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Negative Campus Climate as an Institutional Risk Indicator for Student Success and Wellbeing in Higher Education: A Covariate-Adjusted Analysis of Open Survey Data

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Abstract

Campus climate surveys are widely administered in higher education, but their results are rarely integrated into student-success analytics. This study examines negative campus climate as an institutional risk indicator for academic satisfaction, intention to remain, and psychological wellbeing. Open student microdata from the 2016 University of Michigan Campus Climate Survey on Diversity, Equity and Inclusion (ICPSR 37096) were analyzed. A negative climate factor was constructed from perceived DEI climate, general climate, fair treatment, and institutional communication and showed satisfactory psychometric properties ($KMO = 0.780$; $\alpha = 0.846$; $\omega = 0.850$; $AVE = 0.587$). Survey-weighted analyses combined inverse probability weighting, five-fold cross-fitted augmented inverse probability weighting, continuous models, cluster analysis, mediation, and spline-based risk curves. High negative climate was associated with reductions of 0.734, 0.752, and 0.656 points on the original five-point scales for academic satisfaction, intention to remain, and wellbeing, respectively; standardized AIPW contrasts were -1.029 , -1.017 , and -0.951 SD. Each one SD increase in negative climate was associated with decreases of 0.764, 0.725, and 0.661 SD in the respective outcomes. Wellbeing statistically mediated 21.4% of the association with academic satisfaction and 19.3% of the association with intention to remain. Three interpretable climate profiles showed substantial outcome gradients. The predicted probability of very low outcomes reached 25% at climate scores between 1.80 and 2.42 SD above the mean, depending on the outcome. These context-specific findings support campus climate as a potentially useful institutional monitoring signal, while not establishing temporal or causal effects.

Keywords: campus climate; student success; psychological wellbeing; intention to remain; higher education; diversity, equity and inclusion; propensity-score weighting; augmented inverse probability weighting; institutional risk; learning analytics



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1. Introduction

Higher education institutions increasingly operate in socially, culturally, and demographically diverse environments. Students differ in race and ethnicity, nationality, language, gender identity, socioeconomic background, disability status, prior educational trajectories, and expectations of institutional support. Although this diversity can enrich learning, representation alone does not guarantee inclusion. Students may attend formally diverse institutions while experiencing unfair treatment, weak communication, exclusionary interactions, or limited institutional recognition. Campus climate therefore constitutes

an important feature of the educational environment rather than a peripheral measure of institutional reputation.

Campus climate refers to students' perceptions of whether the institution is fair, inclusive, respectful, responsive, and trustworthy. These perceptions emerge from repeated encounters with faculty, peers, administrative units, institutional communications, and formal and informal norms. The diverse learning environment framework proposes that student outcomes are shaped by interactions among institutional structures, campus cultures, classroom experiences, and intergroup relations (Hurtado et al., 2012). From this perspective, campus climate is an institutional condition interpreted at the student level: it reflects how institutional practices are experienced by those who study within them.

Negative campus climate may function as an institutional risk indicator through several interconnected processes. Perceptions of unfairness, exclusion, or weak institutional responsiveness may reduce belonging and institutional trust, increase psychological strain, and weaken students' academic attachment. Conversely, a fair and inclusive climate may support academic satisfaction, engagement, wellbeing, and willingness to remain enrolled. Longitudinal evidence has established that belonging predicts persistence intentions after accounting for student background and academic integration (Hausmann et al., 2007), while recent studies have connected inclusive campus experiences with engagement, achievement, authenticity, and wellbeing (Berhanu & Sewagegn, 2024; Crawford et al., 2024; Verbree et al., 2025).

Psychological wellbeing is particularly relevant because it may serve as a pathway through which institutional climate becomes academically consequential. Mental health difficulties are common among university students and can affect learning, persistence, and degree completion (Auerbach et al., 2018). Research involving minoritized student populations also indicates that discriminatory climates are associated with greater psychological distress, whereas more favorable climate and belonging are associated with better mental health outcomes (Huang & Fan, 2024; McField et al., 2025; McKenzie et al., 2024). Campus climate may therefore affect academic outcomes both directly and indirectly through students' capacity to thrive within the institution.

Despite this evidence, campus climate information remains weakly integrated into institutional student-success analytics. Learning analytics and early-alert systems generally rely on assessment performance, attendance, learning management system activity, and other behavioral indicators to identify students at risk of failure or withdrawal (Jayaprakash et al., 2014; Akçapınar et al., 2019). Systematic reviews show that these systems can support earlier identification and intervention but also emphasize the limited availability of rigorous, externally validated evidence on their effectiveness (Larrabee Sønderlund et al., 2019; Ifenthaler & Yau, 2020; de Oliveira et al., 2021). Indicators of how students experience fairness, inclusion, and institutional communication are seldom incorporated.

A second limitation is methodological. Much of the campus climate literature is based on descriptive comparisons or conventional regression models. Such studies provide valuable evidence of association but may not sufficiently address observed differences between students reporting more and less negative climates. Propensity-score weighting and doubly robust estimators cannot transform cross-sectional data into an experiment, but they can improve covariate adjustment and clarify the assumptions under which comparisons are made. Likewise, psychometric validation, profile analysis, mediation, and nonlinear risk curves can reveal dimensions of climate that are not captured by a single unvalidated score.

The present study analyzes the public-use student file from the 2016 University of Michigan Campus Climate Survey on Diversity, Equity and Inclusion (ICPSR 37096) (Sellers, 2019). It examines the relationship between a validated negative campus climate factor

and three outcomes: academic satisfaction, intention to remain at the institution, and psychological wellbeing. The study contributes by integrating psychometric validation, survey weighting, inverse probability weighting, cross-fitted augmented inverse probability weighting, continuous models, exploratory climate profiles, statistical mediation, and context-specific risk estimation.

The contribution is theoretical as well as methodological. The study conceptualizes campus climate as an institutional-experience risk indicator linking the diverse learning environment framework with student-success analytics. It does not treat risk as a fixed characteristic located solely within the student. Instead, it examines whether an adverse institutional environment is systematically associated with academic and psychological vulnerability. Because the data are observational, cross-sectional, institution-specific, and prepandemic, the resulting estimates are interpreted as adjusted associations and exploratory monitoring signals rather than causal effects or universal intervention rules.

2. Literature Review

2.1. Campus Climate and Student Outcomes

Campus climate has become a central construct in higher education research because it captures how students experience the university as an institutional, social and academic environment. It is not limited to whether diversity is formally recognized in policies or mission statements; rather, it reflects whether students perceive the institution as fair, respectful, inclusive, communicative and supportive in everyday academic life. In diverse university contexts, these perceptions are especially important because students' experiences of belonging, recognition and fair treatment are shaped not only by classroom instruction, but also by broader institutional signals, peer interactions, administrative practices and the perceived credibility of diversity, equity and inclusion commitments.

Theoretical models of diverse learning environments have emphasized that student outcomes are shaped by the interaction between institutional structures, campus cultures, classroom experiences and intergroup relations (Hurtado et al., 2012). From this perspective, campus climate is not a passive background condition but an active component of the educational environment. Students interpret the university through repeated encounters with faculty, peers, administrative offices, institutional messages and formal or informal norms. When these encounters communicate respect and fairness, students are more likely to perceive the university as a legitimate and supportive learning space. When they communicate exclusion, indifference or unequal treatment, the same institution can become a source of psychological and academic strain.

Empirical studies have consistently associated more positive campus climates with stronger academic engagement, satisfaction and student success. Conversely, negative or discriminatory climates have been linked to lower academic confidence, weaker institutional attachment and poorer wellbeing. Recent research indicates that students from minoritized or international backgrounds may be particularly attentive to climate signals because these signals communicate whether the university recognizes them as full members of the academic community (Golubeva et al., 2025; Wu et al., 2024). In this sense, campus climate is not simply an individual perception; it is a student-level reading of institutional conditions.

A growing body of work has also connected campus climate to achievement and engagement. Studies examining school and university climate suggest that students' perceptions of fairness, support and identification with the institution are associated with academic and wellbeing outcomes over time (Klik et al., 2023). In higher education, similar patterns have been observed in relation to engagement, performance and students' expectations of academic continuity (Berhanu & Sewagegn, 2024; McQueen et al., 2023).

These findings support the idea that climate should be treated as part of the institutional ecology of student success, alongside more traditional predictors such as prior academic preparation, socioeconomic background and engagement behaviors.

However, much of the existing evidence remains descriptive or correlational. Many studies document that campus climate matters, but fewer examine its magnitude as a risk factor or its potential nonlinear relationship with academic and psychological outcomes. This limitation is important because institutional leaders do not only need to know whether climate is associated with student outcomes; they also need to know how strongly it matters, whether its effects intensify at more negative levels and whether particular climate profiles identify groups of students who may require closer institutional attention. Addressing this issue requires moving beyond broad climate descriptions toward analytic models capable of estimating gradients, thresholds and policy-relevant risk zones.

2.2. Wellbeing, Belonging and Persistence

Student success in higher education has traditionally been measured through academic performance, retention and completion. While these indicators remain important, they provide an incomplete view of students' educational trajectories. A student may remain enrolled while experiencing low satisfaction, weak belonging or deteriorating wellbeing. Conversely, students who feel valued, supported and psychologically secure are more likely to engage with the institution, persist through academic difficulties and perceive their studies as meaningful. For this reason, wellbeing and belonging have become central concepts in contemporary higher education research.

Belonging is particularly relevant because it connects the social and psychological dimensions of campus life with academic persistence. Longitudinal evidence has shown that students' sense of being a valued member of the university community predicts intentions to persist, even after controlling for background characteristics and academic integration (Hausmann et al., 2007). This finding is important because it shows that persistence is not only a function of grades, motivation or financial resources. It is also shaped by whether students perceive themselves as legitimate members of the institution.

Recent work has expanded this argument by showing that belonging, authenticity and inclusive institutional experiences are associated with academic performance, motivation and wellbeing across different student populations (Crawford et al., 2024; Jones & Bell, 2025; Verbree et al., 2025). These studies suggest that belonging functions as a psychological bridge between the university environment and student outcomes. When students feel that they can participate without concealing central aspects of their identity or background, the institution becomes more conducive to learning. When students experience marginalization, invisibility or unfair treatment, their academic and psychological resources may be depleted.

Wellbeing is also increasingly recognized as a core outcome of higher education rather than a secondary concern. International evidence has drawn attention to the prevalence of psychological distress among university students and its implications for learning, persistence and degree completion (Auerbach et al., 2018). This does not mean that universities are solely responsible for all dimensions of student wellbeing, but it does mean that institutional environments can either buffer or intensify student vulnerability. Campus climate is one of the mechanisms through which the institution becomes psychologically consequential.

Evidence linking DEI initiatives, climate and mental health reinforces this point. McField et al. (2025) found that the relationship between institutional DEI initiatives and mental health outcomes among LGBTQ+ students was explained through more positive perceptions of campus climate and stronger sense of belonging. Similarly, Huang and Fan (2024) reported that discriminatory campus climates are associated with higher psycholog-

ical distress among LGBTQ+ students. Research on Asian American graduate students has also highlighted the role of campus climate and belonging in mental health outcomes (McKenzie et al., 2024). These findings suggest that wellbeing is not simply an outcome parallel to academic satisfaction and persistence; it may also operate as a pathway through which campus climate affects academic trajectories.

This relationship is especially relevant for institutional monitoring. If negative campus climate reduces wellbeing, and wellbeing in turn contributes to lower academic satisfaction or weaker intention to remain, then climate data can help institutions identify not only dissatisfied students but also underlying mechanisms of risk. In this sense, wellbeing should not be treated merely as an individual psychological variable. It should be understood as part of the broader institutional process through which students interpret whether the university is a place where they can thrive.

2.3. Learning Analytics and Early-Warning Systems

Learning analytics and early-warning systems have developed as institutional responses to the need for timely, data-informed student support. These systems typically use academic records, learning management system activity, attendance, assessment performance or engagement indicators to estimate the probability that a student may fail, withdraw or underperform. Their main contribution is practical: they translate student data into actionable signals that can guide advising, tutoring, mentoring and other forms of intervention.

A foundational example is the work of Jayaprakash et al. (2014), who presented an open-source early-alert initiative to identify academically at-risk students. Since then, early-warning approaches have become increasingly sophisticated, incorporating predictive modeling, risk classification and intervention workflows. In most cases, however, the predictors used in such systems remain heavily academic or behavioral. They focus on what students do in courses, how often they access learning platforms, whether they submit assignments or how they perform in assessments. These indicators are valuable, but they do not fully capture how students experience the institution.

Subsequent empirical studies and systematic reviews have shown that learning analytics systems can support the identification of students who may require timely assistance, but they also reveal substantial variation in predictor selection, validation practices, intervention design, and evidence of effectiveness (Akçapınar et al., 2019; Larrabee Sönderlund et al., 2019; Ifenthaler & Yau, 2020; de Oliveira et al., 2021). In particular, accurate risk classification does not by itself demonstrate that an analytics-informed intervention improves retention, learning, or wellbeing. External validation, transparent intervention protocols, and evaluation of potential unintended consequences remain necessary before such systems are transferred across institutional contexts.

This creates a blind spot. A student may be academically active but still experience the campus climate as unfair, exclusionary or psychologically unsafe. Another student may show declining engagement partly because the institutional environment has weakened their belonging or wellbeing. If early-warning systems ignore climate, they may identify academic risk only after it has become visible in grades or behavior. Campus climate indicators could therefore complement traditional learning analytics by capturing institutional and psychosocial sources of risk before they appear as academic failure.

The integration of campus climate into risk monitoring requires a conceptual shift. Climate surveys are often used for institutional reporting, strategic planning or DEI assessment, but they are rarely connected to student-success analytics. As a result, climate data may remain descriptive and retrospective. Reports may show that some groups experience the university less positively, but they do not necessarily estimate how climate relates to

specific academic and wellbeing risks or identify the levels of climate deterioration that should trigger institutional concern.

A more integrated approach would treat campus climate as an institutional risk indicator. Under this framework, climate data would not replace academic early-alert models but would enrich them. Academic records can indicate performance risk; learning analytics can indicate engagement risk; and climate data can indicate institutional-experience risk. Combining these perspectives would allow universities to understand not only which students are at risk, but also whether part of that risk is associated with modifiable institutional conditions such as fair treatment, communication, inclusion and perceived support.

2.4. Gap: Lack of Climate-Informed Risk Thresholds

Despite the growing evidence linking campus climate, belonging, wellbeing and student outcomes, an important gap remains: the field has limited knowledge about climate-informed risk thresholds. Most studies show that negative climate is associated with worse outcomes, but they rarely estimate the point at which the probability of serious academic dissatisfaction, low intention to remain or poor wellbeing becomes institutionally meaningful. This is a major limitation for policy and practice.

Universities need interpretable thresholds because institutional action requires prioritization. It is not enough to know that climate is negatively associated with satisfaction or persistence. Administrators, student-success units and DEI offices need to know when climate deterioration becomes severe enough to justify closer monitoring, targeted diagnosis or preventive intervention. Without empirically grounded thresholds, climate surveys may identify general problems but fail to support timely and proportionate responses.

The absence of climate-informed thresholds is also methodological. Campus climate is often modeled as a single scale or as a set of separate survey items. This approach can obscure latent patterns in students' experiences. For example, two students may report similar overall climate scores but differ in whether their concerns relate mainly to fair treatment, general institutional climate or communication. Recent studies have emphasized the importance of belonging, campus climate and mental health outcomes, but less attention has been given to whether distinct climate profiles can be linked to graded academic and wellbeing risks (Crawford et al., 2024; Jones & Bell, 2025; McKenzie et al., 2024).

There is also a causal-inference gap. Observational climate surveys are not experiments, and their results should not be interpreted as if students had been randomly assigned to positive or negative institutional environments. There is also an inferential gap. Observational campus climate surveys are not experiments, and their findings should not be interpreted as if students had been randomly assigned to positive or negative institutional environments. Modern covariate-adjustment methods, including propensity-score weighting and augmented inverse probability weighting, can reduce observed imbalance and make the assumptions underlying comparisons more transparent. However, these methods do not establish causal effects in cross-sectional data and cannot eliminate unmeasured confounding, reverse causality, or common-method bias. Their contribution in the present study is therefore to provide more defensible adjusted associations than unweighted descriptive comparisons. (Chesnaye et al., 2022; Funk et al., 2011; Liu et al., 2016; Qin, 2024).

The present study responds to these gaps by connecting campus climate research with institutional risk monitoring. It conceptualizes negative campus climate as a latent factor derived from students' perceptions of DEI climate, general campus climate, fair treatment and institutional communication. It then examines this factor in relation to academic satisfaction, intention to remain and psychological wellbeing using inverse probability weighting, doubly robust estimation, continuous dose-response models, mediation

analysis, climate-profile clustering and risk-threshold curves. This design allows the study to address a question that remains insufficiently developed in the literature: not only whether campus climate matters, but how strongly it matters, through which pathway it may operate and at what levels it becomes a measurable institutional risk for student success and wellbeing.

2.5. Research Questions and Hypotheses

The study addresses the following research questions:

RQ1. *To what extent is negative campus climate associated with academic satisfaction, intention to remain, and psychological wellbeing after adjustment for the observed student characteristics available in the public-use dataset?*

RQ2. *Do adverse associations become stronger at more negative climate levels, and do interpretable profiles of campus climate perceptions correspond with graded student outcomes?*

RQ3. *Does psychological wellbeing statistically mediate part of the association between negative campus climate and academic satisfaction or intention to remain?*

RQ4. *At what negative climate values do the estimated probabilities of very low academic satisfaction, very low intention to remain, and very low wellbeing reach substantively interpretable levels within the observed sample?*

The following hypotheses were specified:

H1a. *Higher negative campus climate will be associated with lower academic satisfaction.*

H1b. *Higher negative campus climate will be associated with lower intention to remain at the institution.*

H1c. *Higher negative campus climate will be associated with lower psychological wellbeing.*

H2. *The magnitude of the adverse adjusted associations will increase when high negative climate is defined using more stringent cutoffs, and continuous climate models will show negative gradients across all three outcomes.*

H3. *Students assigned to more negative climate profiles will report lower academic satisfaction, intention to remain, and psychological wellbeing than students assigned to more positive profiles.*

H4. *Psychological wellbeing will statistically mediate part, but not all, of the association between negative climate and the two academic outcomes.*

H5. *The estimated probability of very low student outcomes will increase nonlinearly in the extreme negative tail of the climate distribution, although the resulting probability reference points will be institution- and period-specific.*

3. Materials and Methods

3.1. Research Design, Data Source and Variables

This study conducted a secondary cross-sectional analysis of open survey microdata from the University of Michigan Campus Climate Survey on Diversity, Equity and Inclusion, ICPSR 37096 (Sellers, 2019). The survey was administered at the University of Michigan–Ann Arbor, a large public research-intensive institution enrolling undergraduate, graduate,

and professional students. The student survey was collected between September and December 2016. The year 2019 refers to the release of the ICPSR data record rather than the year of data collection.

The survey was designed to assess diversity, equity, inclusion, intergroup relations, fair treatment, discrimination, and related educational experiences across the institution's undergraduate, graduate, and professional student population. However, the public-use file masks detailed race/ethnicity and academic unit identifiers; consequently, the present study can describe the institutional and academic context but cannot reproduce a complete demographic diversity profile or evaluate fine-grained intersectional patterns.

The original student component was drawn from a stratified random sample of 3500 enrolled students, with 1800 completed student records included in the public-use file. The unweighted student response rate was 51%, and the weighted response rate was 59% (Sellers, 2019). The supplied student weight, WGT_STUD, expanded the public-use sample to a student population estimate of 44,879. The weighting variable was incorporated into descriptive summaries and model estimation. Because strata and primary sampling-unit identifiers were unavailable in the public-use file, the data were analyzed as a weighted single-stage survey rather than as a fully specified complex survey design.

Complete information on the four climate indicators was available for 1418 students, representing 35,920 weighted students or 80.0% of the full weighted population. The final outcome-specific samples contained 1417 students for academic satisfaction, 1415 for intention to remain, and 1417 for psychological wellbeing. Complete-case selection diagnostics indicated composition differences between included and excluded observations, particularly for undergraduate and enrollment status; this possibility of selection bias is considered in the interpretation of the findings.

The principal exposure was perceived negative campus climate. It was constructed from four five-point indicators: perceived diversity, equity and inclusion climate (SURV_CLIMATEDEI), general campus climate (SURV_CLIMATEGEN), fair treatment (SURV_FAIRTREAT), and institutional communication (SURV_INSTCOM). Higher original values represented more positive perceptions.

The standardized indicators were submitted to maximum-likelihood exploratory factor analysis. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin statistic, and factorability was assessed through Bartlett's test of sphericity. The number of factors was evaluated through parallel analysis based on 2000 random datasets. Internal consistency and convergent validity were assessed using Cronbach's alpha, approximate omega total, composite reliability, average variance extracted, factor loadings, communalities, and corrected item–total correlations.

A one-factor score was retained and reverse-oriented so that higher values indicated more negative campus climate. The score was standardized as *climate_factor_z*, with one unit representing one standard deviation in the negative climate construct. Observations without a valid factor score were not classified as members of either exposure group.

Academic satisfaction was measured using V33, intention to remain using V35, and psychological wellbeing using SURV_THRIVEGROW. All three outcomes were available on their original five-point scales. Main adjusted contrasts were reported both in original-scale points and after survey-weighted standardization. For risk estimation, an adverse binary outcome was defined as an original score of 2 or lower.

The public-use file masked several identity and institutional variables. Consequently, race/ethnicity and campus unit could not be modeled as substantive multi-category covariates. Other listed fields were constant or fully masked in the analytic file. The usable adjustment set therefore consisted of gender category (UM_SEX), undergraduate status (UM_UNDERGRAD), and enrollment category (STU_ENROLL). The category labels sup-

plied by the public-use file were retained, and no substantive identity interpretation was assigned to masked or anonymized codes.

3.2. Analytical Strategy

The analysis integrated psychometric validation, survey-weighted description, propensity-score adjustment, continuous regression, exploratory clustering, statistical mediation, and nonlinear risk estimation. All analyses were conducted using the student survey weight. The objective was to obtain more defensible covariate-adjusted associations than unweighted comparisons, not to establish experimental causality.

First, weighted descriptive statistics were calculated for the full analytic sample and across weighted tertiles of the negative climate factor. These comparisons examined whether academic satisfaction, intention to remain, and wellbeing followed an ordered gradient as climate became more negative.

Second, a high-negative-climate exposure indicator was defined as $\text{climate_factor_z} \geq 0$. This contrast compared students at or above the mean of the negative climate factor with students below the mean. Propensity scores were estimated using weighted logistic regression with UM_SEX, UM_UNDERGRAD, and STU_ENROLL as predictors.

Inverse probability weighting was used as a conventional sensitivity estimator. The primary estimator was five-fold cross-fitted augmented inverse probability weighting (AIPW). Within each training fold, the propensity score was estimated using logistic regression, and separate outcome models for the high-negative-climate and comparison groups were estimated using random forests. Predictions were generated only for the corresponding held-out fold. Cross-fitting reduced the risk that the doubly robust estimator would rely on in-sample nuisance-model predictions.

Propensity scores were truncated to the interval [0.01, 0.99]. AIPW estimates were obtained from the weighted mean of the augmented pseudo-outcome. Approximate 95% confidence intervals were calculated from its weighted variance using the effective sample size. Estimates were reported in original five-point scale units and in survey-weighted standard-deviation units.

Observed-covariate balance was assessed through standardized mean differences before and after weighting. Absolute SMD values below 0.10 were considered evidence of acceptable observed balance. Positivity and common support were assessed through the propensity-score distributions, proportions below 0.05 or above 0.95, and inverse-probability-weight effective sample sizes. These diagnostics evaluate only the measured covariates and cannot establish balance in unobserved characteristics.

Third, cutoff sensitivity analyses used two theoretical thresholds: $z \geq 0.674$, corresponding to the 75th percentile of a standard normal distribution, and $z \geq 0.842$, corresponding to its 80th percentile. To assess whether results depended on the normal-distribution reference, the analyses were repeated using the empirical 75th and 80th percentiles of the observed factor distribution, $z = 0.594$ and $z = 0.833$, respectively.

Continuous associations were estimated using survey-weighted least squares with heteroskedasticity-consistent HC3 standard errors. Each standardized outcome was regressed on climate_factor_z and the observed adjustment variables. The resulting coefficient represents the expected change in outcome standard deviations associated with a one-standard-deviation increase in negative campus climate. Reported R^2 values refer to the full-adjusted models rather than to climate alone.

Exploratory subgroup-specific AIPW estimates were calculated separately within the available gender and undergraduate-status categories. These analyses examined consistency of direction and magnitude but were not interpreted as formal statistical tests of between-group effect modification.

Fourth, *k*-means clustering was applied to the four standardized climate indicators. The derived factor was not included as a clustering input because it was constructed from those same indicators; it was used only to order the resulting profiles from positive to negative. Solutions from $k = 2$ to $k = 8$ were evaluated using silhouette width, Calinski–Harabasz index, Davies–Bouldin index, minimum cluster proportion, and bootstrap stability. Stability was assessed through 200 resamples using the adjusted Rand index.

The two-cluster solution provided the strongest internal separation, whereas the three-cluster solution produced the highest mean bootstrap stability and an interpretable positive–intermediate–negative gradient. Because the clustering objective was exploratory and profile-oriented, the three-cluster solution was retained for substantive presentation. The more parsimonious two-cluster solution and the full model-selection diagnostics were retained as sensitivity evidence.

Fifth, psychological wellbeing was examined as a statistical mediator of the associations between negative climate and academic satisfaction or intention to remain. Survey-weighted linear mediation models used standardized exposure, mediator, and outcome variables. Direct, indirect, and total associations were estimated, and 95% confidence intervals were obtained from 2000 bootstrap replications. Given the cross-sectional design, these results are interpreted as a plausible statistical pathway rather than evidence of temporal or causal mediation.

Finally, weighted spline-logistic models estimated the probability of academic satisfaction ≤ 2 , intention to remain ≤ 2 , and wellbeing ≤ 2 across the climate distribution. A cubic B-spline with four degrees of freedom allowed the probability curve to vary non-linearly. Predicted probabilities and 95% confidence intervals were generated within the observed 1st–99th percentile range of climate_factor_z. Values at which the estimated probability reached 25% or 50% were identified as descriptive reference points. They were not treated as universal thresholds, validated classification rules, or automatic triggers for individual-level intervention.

3.3. Inferential Scope and Methodological Caution

The potential-outcome framework informed the covariate-adjusted contrasts, but the study does not establish causal identification. Campus climate was not randomly assigned, exposure and outcomes were measured at the same time, and conditional exchangeability cannot be verified. IPW and cross-fitted AIPW improve adjustment for the observed variables available in the public-use file, but they cannot remove residual confounding, reverse causality, or bias from omitted variables.

The survey relies on self-reported climate perceptions and self-reported outcomes, which may generate common-method variance. Students experiencing lower wellbeing or satisfaction may also evaluate the institution more negatively, making the direction of association uncertain. Longitudinal measurements are needed to determine whether changes in climate precede changes in wellbeing, satisfaction, or persistence.

The public-use file masks race/ethnicity, institutional unit, and other characteristics. This restriction is especially important because campus climate experiences may differ substantially across social identities and institutional locations. The study therefore cannot evaluate intersectional heterogeneity or determine whether the overall estimates conceal greater vulnerability in particular racial, ethnic, gender identity, disability, international student, or academic unit groups.

Approximately 20% of the weighted student population lacked complete information for the climate factor or focal outcomes. Included and excluded cases differed in undergraduate and enrollment composition, indicating possible complete-case selection bias.

Survey weighting addresses the supplied sampling and nonresponse adjustments but does not necessarily correct this outcome-specific complete-case selection.

The study concerns one large public research university in the United States. Its institutional mission, size, demographic composition, governance, and DEI context may differ from those of community colleges, teaching-focused institutions, private universities, or institutions in other national systems. External validity must therefore be established through replication.

The data were collected in 2016, before the COVID-19 pandemic. Subsequent changes in remote and hybrid learning, student wellbeing, institutional communication, social interaction, and perceptions of belonging may have altered both the prevalence and consequences of negative campus climate. The estimated probability reference points should therefore be treated as institution- and period-specific.

Finally, the risk models were not evaluated prospectively in a new cohort and were not externally calibrated. They illustrate how climate data might contribute to institutional monitoring, but they are not suitable for diagnostic labeling or automated individual-level decision-making. Operational use would require longitudinal validation, fairness assessment, calibration, evaluation of interventions, and appropriate student-data governance.

4. Results

4.1. Measurement and Analytical-Sample Diagnostics

The full public-use student file contained 1800 observations and represented 44,879 weighted students. Complete information for all four climate indicators was available for 1418 respondents, representing 35,920 weighted students or 80.0% of the full weighted population. The outcome-specific analytic samples contained 1417 respondents for academic satisfaction, 1415 for intention to remain, and 1417 for wellbeing.

Missingness was concentrated in academic satisfaction, intention to remain, and fair treatment, each of which had approximately 20% weighted missing information. Comparisons between complete and excluded observations showed relatively small differences for gender category but larger differences for undergraduate status and enrollment category, with maximum weighted SMDs of 0.377 and 0.381, respectively. These results indicate that complete-case selection may have altered the academic-level composition of the analytic sample.

The psychometric diagnostics supported a one-factor representation of the four campus climate indicators. The overall KMO was 0.780, and Bartlett's test rejected the null hypothesis that the indicator correlation matrix was an identity matrix, $\chi^2(6) = 2458.14$, $p < 0.001$. Cronbach's alpha was 0.846, approximate omega total and composite reliability were both 0.850, and average variance extracted was 0.587. The factor accounted for 58.7% of the common standardized variance.

As shown in Table 1, all indicators had substantial absolute loadings, ranging from 0.711 to 0.861, with communalities between 0.506 and 0.742. The negative signs reflect the positive orientation of the original survey indicators; the derived factor was subsequently reverse-oriented so that higher scores represented more negative climate.

Psychometric diagnostics supported retention of a single factor. As shown in Figure 1, only the first observed eigenvalue exceeded the 95th percentile obtained from the parallel analysis, and all four indicators displayed substantial absolute loadings on the retained factor.

Table 1. Psychometric properties of the negative campus climate factor.

Indicator	Standardized Loading	Communality	Uniqueness	Corrected Item–Total Correlation
DEI climate	−0.861	0.742	0.258	0.762
General campus climate	−0.768	0.590	0.410	0.691
Institutional communication	−0.714	0.510	0.490	0.635
Fair treatment	−0.711	0.506	0.494	0.653

Note: $n = 1418$. Maximum-likelihood exploratory factor analysis. Overall KMO = 0.780; Bartlett's $\chi^2(6) = 2458.14$, $p < 0.001$; Cronbach's $\alpha = 0.846$; approximate $\omega = 0.850$; composite reliability = 0.850; AVE = 0.587. The retained factor accounted for 58.7% of the standardized variance. Parallel analysis retained one factor.

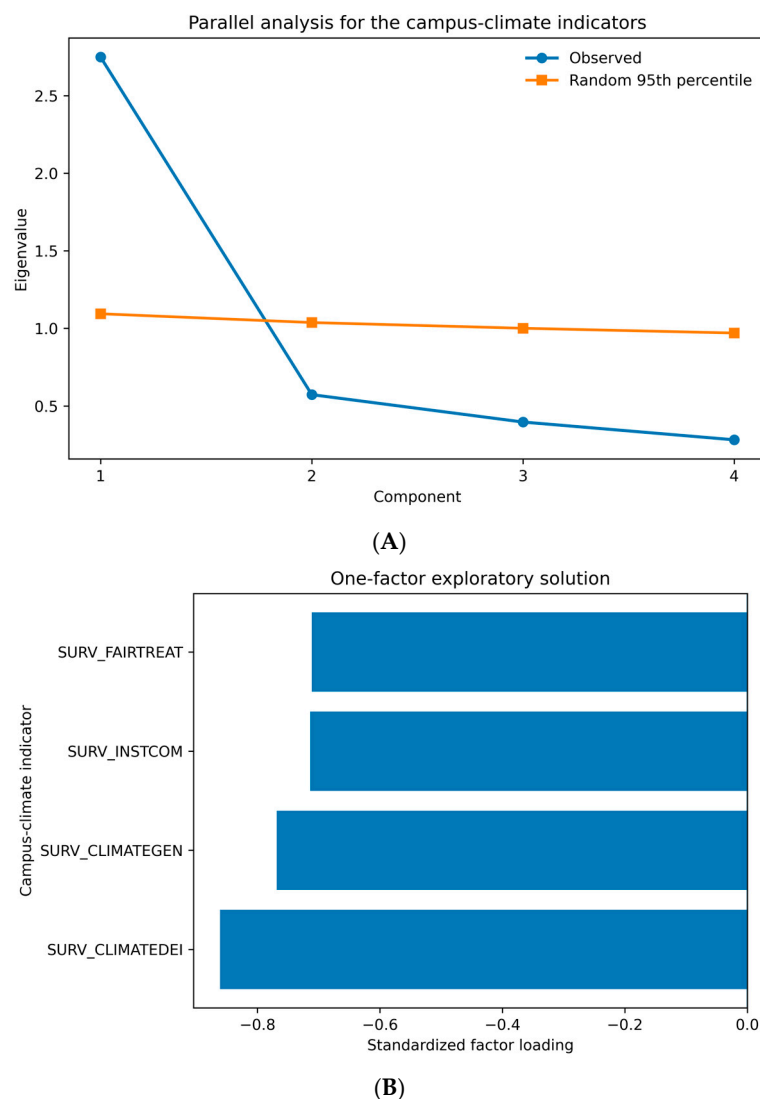


Figure 1. Psychometric diagnostics for the negative campus climate factor. **(A)** Parallel analysis comparing observed eigenvalues with the 95th percentile of eigenvalues from 2000 random datasets. Only the first component satisfied the retention criterion. **(B)** Standardized maximum-likelihood factor loadings for the four campus climate indicators. Negative signs reflect the orientation of the original indicators toward positive climate; the derived factor was reverse-oriented so that higher scores indicate more negative campus climate.

4.2. Descriptive Climate–Outcome Gradients

Table 2 presents the main IPW and cross-fitted AIPW contrasts. On the original scales, high negative climate was associated with a 0.734-point reduction in academic satisfaction,

a 0.752-point reduction in intention to remain, and a 0.656-point reduction in wellbeing. The corresponding standardized AIPW contrasts were -1.029 SD, -1.017 SD, and -0.951 SD.

Table 2. IPW and cross-fitted AIPW contrasts for high negative campus climate.

Outcome	N	IPW Contrast, Original Scale	AIPW Contrast, Original Scale (95% CI)	IPW Contrast, SD	AIPW Contrast, SD (95% CI)
Academic satisfaction	1417	−0.735	−0.734 [−0.824, −0.644]	−1.030	−1.029 [−1.155, −0.903]
Intention to remain	1415	−0.749	−0.752 [−0.848, −0.657]	−1.013	−1.017 [−1.146, −0.888]
Psychological wellbeing	1417	−0.658	−0.656 [−0.743, −0.569]	−0.954	−0.951 [−1.077, −0.825]

Note: High negative climate was defined as $\text{climate_factor_}z \geq 0$. Original-scale estimates represent points on the corresponding five-point scale. Standardized estimates use the survey-weighted outcome standard deviation. AIPW estimates used five-fold cross-fitting.

The close agreement between IPW and AIPW estimates indicates that the substantive conclusions were not sensitive to the choice between the conventional weighting estimator and the cross-fitted doubly robust estimator. All AIPW confidence intervals excluded zero.

Balance and overlap diagnostics are presented in Figure 2. Before weighting, the largest observed imbalance was found for gender category, with an absolute survey-weighted SMD of 0.411. After weighting, all observed-covariate SMDs were below 0.002 in absolute value. For the primary exposure definition, no propensity scores were below 0.05 or above 0.95, and the effective sample sizes ranged from approximately 802 to 819 across outcomes.

Cutoff sensitivity analyses supported a graded association (Figure 3). The theoretical cutoffs $z = 0.674$ and $z = 0.842$ correspond to the 75th and 80th percentiles of a standard normal distribution. For academic satisfaction, the standardized AIPW contrast increased in magnitude from -1.029 SD at $z \geq 0$ to -1.321 SD at $z \geq 0.674$ and -1.461 SD at $z \geq 0.842$. The corresponding contrasts were -1.017 , -1.223 , and -1.324 SD for intention to remain and -0.951 , -1.156 , and -1.213 SD for wellbeing.

The empirical 75th- and 80th-percentile cutoffs were $z = 0.594$ and $z = 0.833$, respectively. Estimates based on these observed percentiles were similar to those based on the theoretical standard normal cutoffs, indicating that the increasing magnitude was not an artifact of the selected reference distribution.

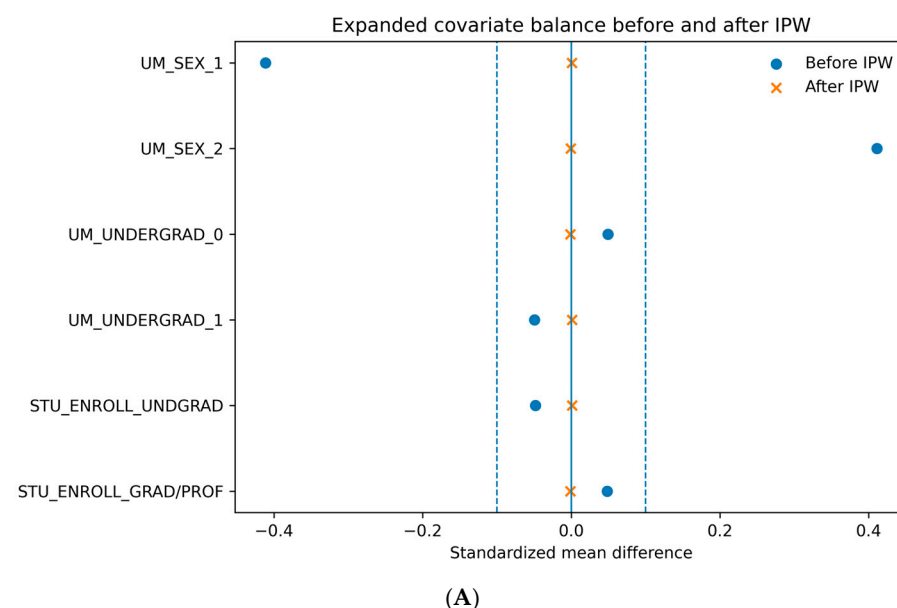


Figure 2. Cont.

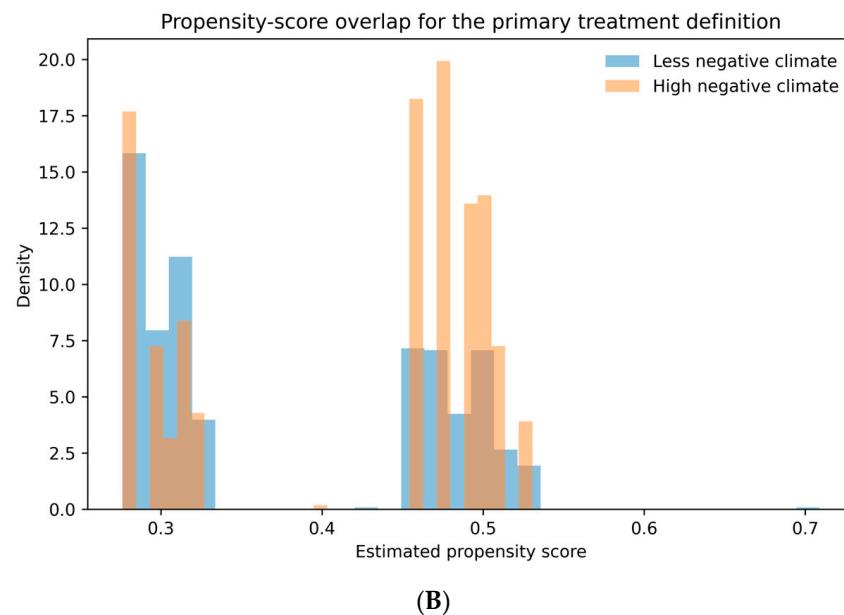


Figure 2. Balance and overlap diagnostics for the primary high-negative-climate exposure definition. (A) Standardized mean differences before and after inverse probability weighting in the academic satisfaction analytic sample. Dashed lines at ± 0.10 denote the conventional observed-balance criterion. (B) Propensity-score distributions for the high-negative-climate and comparison groups. Patterns were comparable across outcome-specific samples.

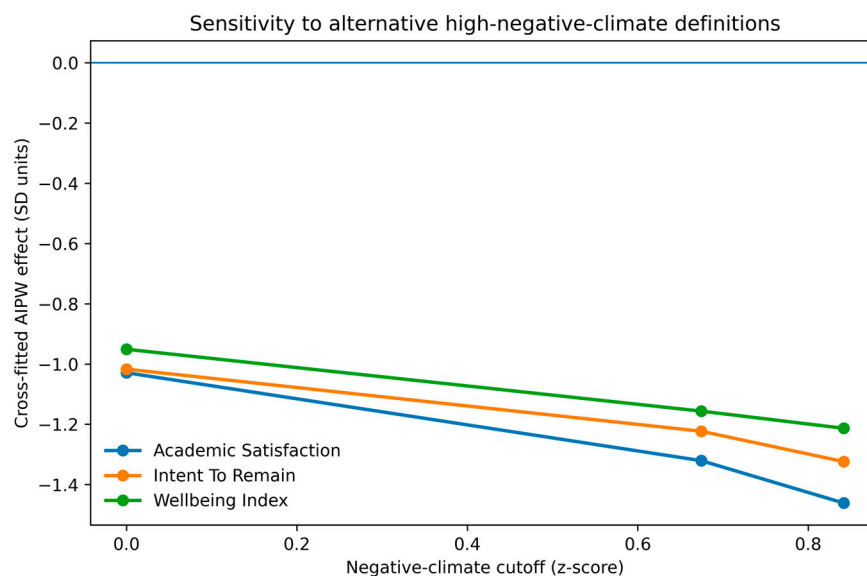


Figure 3. Sensitivity of cross-fitted AIPW estimates to alternative high-negative-climate definitions. Cutoffs at $z \geq 0$, $z \geq 0.674$, and $z \geq 0.842$ correspond to the mean, the theoretical upper quartile, and the theoretical upper quintile of a standard normal distribution. More negative estimates indicate larger adverse adjusted contrasts. Estimates are reported in survey-weighted standard-deviation units.

The continuous models provided further evidence of graded associations. As shown in Table 3, each one-standard-deviation increase in negative campus climate was associated with a 0.764 SD reduction in academic satisfaction, a 0.725 SD reduction in intention to remain, and a 0.661 SD reduction in wellbeing. All associations were statistically distinguishable from zero.

Table 3. Continuous adjusted associations between negative climate and standardized outcomes.

Outcome	N	Standardized Coefficient	HC3 Robust SE	95% CI	p-Value	Full-Model (R^2)
Academic satisfaction	1417	−0.764	0.027	[−0.817, −0.711]	<0.001	0.485
Intention to remain	1415	−0.725	0.028	[−0.781, −0.669]	<0.001	0.436
Psychological wellbeing	1417	−0.661	0.033	[−0.726, −0.596]	<0.001	0.356

Note: Coefficients represent change in outcome standard deviations per one-standard-deviation increase in negative campus climate. Models were estimated using survey-weighted least squares with HC3 robust standard errors and adjusted for the usable public-file covariates.

The full-adjusted models' SD reduction in academic satisfaction had R^2 values of 0.485, 0.436, and 0.356, respectively. These values represent the explanatory performance of the complete models, including climate and the adjustment covariates.

Exploratory subgroup-specific AIPW estimates were consistently negative across the available gender and undergraduate-status categories. Standardized estimates ranged from −0.877 to −1.080 SD, and all corresponding 95% confidence intervals excluded zero.

4.3. Exploratory Campus Climate Profiles and Statistical Mediation

The internal clustering indices did not identify a single solution that dominated every criterion. The two-cluster solution had the highest silhouette coefficient (0.366), highest Calinski–Harabasz index (1105.67), and lowest Davies–Bouldin index (1.045), indicating stronger internal separation. The three-cluster solution had a lower silhouette coefficient (0.281) but the highest mean bootstrap-adjusted Rand index (0.834), adequate minimum cluster size, and a substantively interpretable positive–intermediate–negative gradient.

Accordingly, the three-cluster solution was retained as an exploratory profile representation, while the two-cluster solution was recognized as the more parsimonious alternative.

The weighted profiles are presented in Table 4. Percentages were calculated among the 1418 cluster-complete observations and therefore sum to 100%. The positive profile represented 33.2% of the weighted cluster-complete sample, the intermediate profile 48.5%, and the negative profile 18.3%.

The profiles showed clear outcome gradients. Compared with the positive profile, the negative profile had academic satisfaction lower by approximately 1.33 points, intention to remain lower by 1.32 points, and wellbeing lower by 1.08 points. Figure 4 displays the standardized climate-indicator configuration of the retained exploratory profiles.

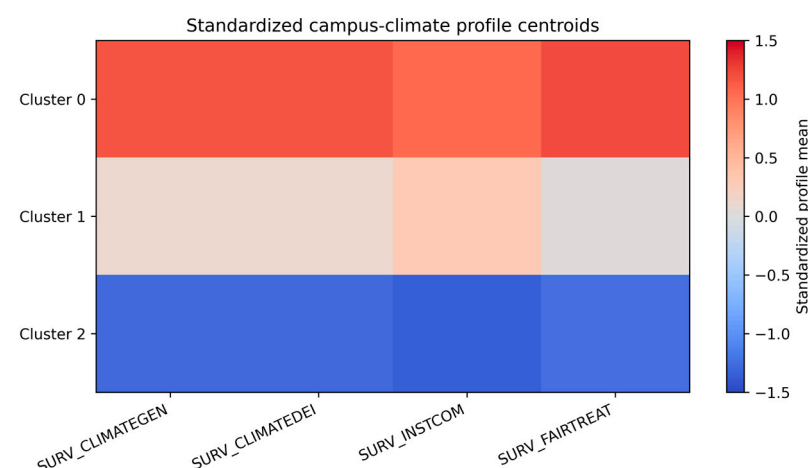


Figure 4. Standardized indicator means for the exploratory three-profile campus climate solution. Clusters were estimated from the four standardized climate indicators; the derived negative climate factor was not used as an input. The profiles were ordered from positive to negative using the external factor score. The two-cluster solution provided stronger internal separation, whereas the three-cluster solution showed the highest mean bootstrap stability and yielded an interpretable positive–intermediate–negative gradient.

Table 4. Validated three-profile campus climate solution.

Profile	Unweighted <i>n</i>	Weighted <i>N</i>	Weighted %	DEI Climate	General Climate	Fair Treatment	Institutional Communication	Negative Climate Factor <i>z</i>	Academic Satisfaction	Intention to Remain	Wellbeing
Positive climate	419	11,942	33.2	4.46	4.28	4.70	3.94	−1.10	4.69	4.69	4.33
Intermediate climate	655	17,412	48.5	3.68	3.63	4.02	3.41	−0.06	4.02	3.98	3.80
Negative climate	344	6565	18.3	2.65	2.87	3.43	2.29	1.30	3.36	3.38	3.25

Note: *K*-means inputs were the four standardized climate indicators. The negative climate factor was not included as a clustering input and was used only to order the profiles. Percentages refer to the weighted cluster-complete sample and sum to 100%.

Psychological wellbeing statistically mediated part of the association between negative climate and both academic outcomes. For academic satisfaction, the standardized indirect association was -0.164 (95% CI $[-0.206, -0.122]$), the direct association was -0.600 (95% CI $[-0.665, -0.532]$), and the total association was -0.763 (95% CI $[-0.816, -0.710]$). The estimated mediated proportion was 21.4%.

For intention to remain, the indirect association was -0.140 (95% CI $[-0.184, -0.097]$), the direct association was -0.585 (95% CI $[-0.650, -0.520]$), and the total association was -0.725 (95% CI $[-0.779, -0.670]$). The estimated mediated proportion was 19.3%. These results are consistent with partial statistical mediation but do not establish that climate temporally preceded wellbeing or that wellbeing causally preceded the academic outcomes (Table 5).

Table 5. Statistical mediation through psychological wellbeing.

Outcome	N	Climate → Wellbeing, <i>a</i>	Wellbeing → Outcome, <i>b</i>	Indirect Association (95% CI)	Direct Association (95% CI)	Total Association (95% CI)	Proportion Statistically Mediated
Academic satisfaction	1416	-0.664	0.246	$-0.164 [-0.206, -0.122]$	$-0.600 [-0.665, -0.532]$	$-0.763 [-0.816, -0.710]$	21.4%
Intention to remain	1414	-0.664	0.211	$-0.140 [-0.184, -0.097]$	$-0.585 [-0.650, -0.520]$	$-0.725 [-0.779, -0.670]$	19.3%

Note: Exposure, mediator, and outcomes were survey-weight standardized. Confidence intervals were obtained from 2000 successful bootstrap replications. The decomposition represents statistical mediation in cross-sectional data.

4.4. Context-Specific Risk Reference Points

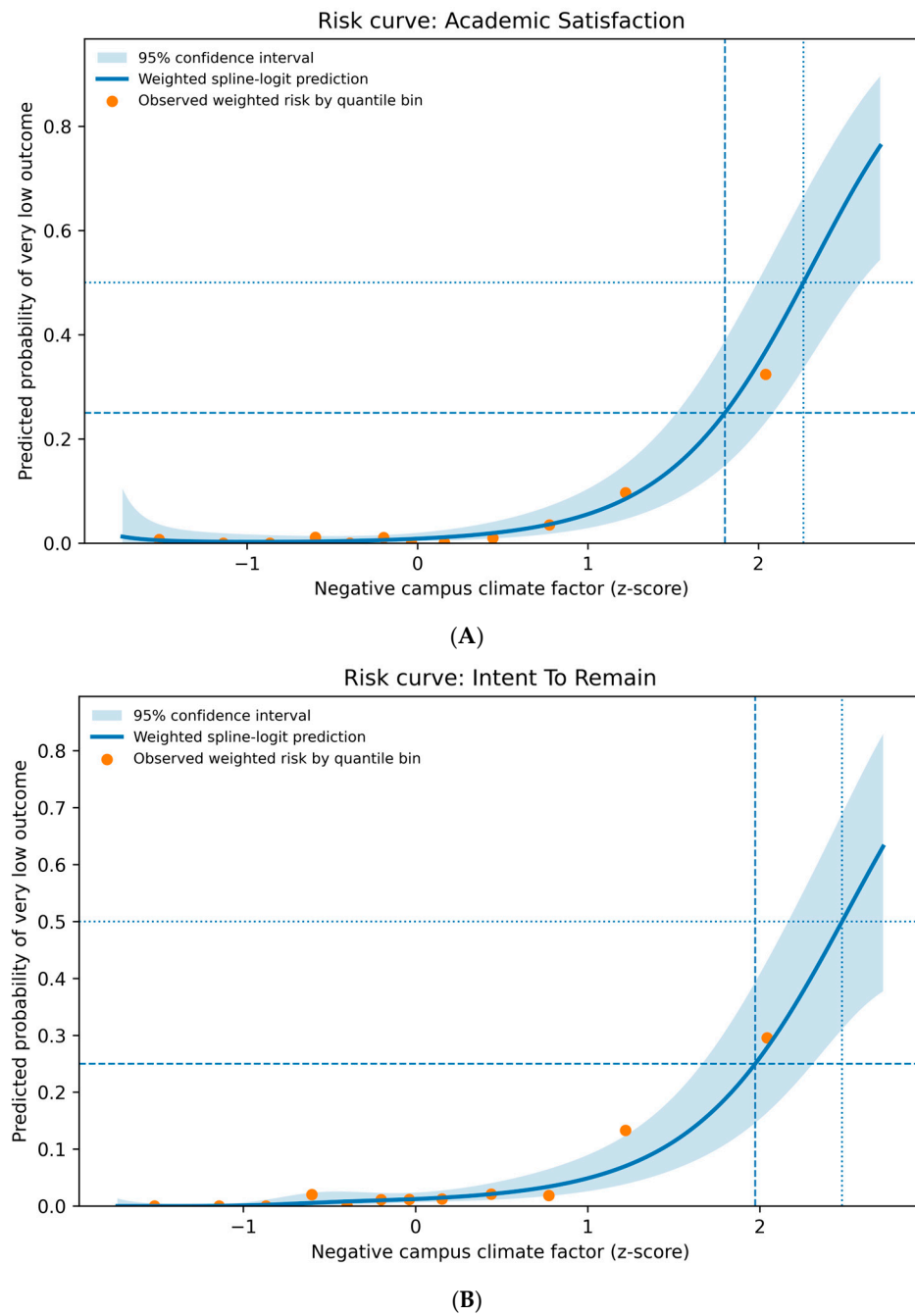
The spline-logistic risk curves showed that the estimated probabilities of very low outcomes remained low across most of the climate distribution and increased in its extreme negative tail (Table 6). The weighted observed prevalence was 3.0% for very low academic satisfaction, 3.2% for very low intention to remain, and 1.7% for very low wellbeing.

Table 6. Context-specific climate-risk reference points.

Outcome	N	Adverse-Outcome Definition	Weighted Prevalence	Climate <i>z</i> at 25% Estimated Risk	Climate <i>z</i> at 50% Estimated Risk	Maximum Predicted Risk Within Observed Range
Academic satisfaction	1417	$V33 \leq 2$	3.0%	1.80	2.26	76.2%
Intention to remain	1415	$V35 \leq 2$	3.2%	1.97	2.48	63.1%
Psychological wellbeing	1417	$SURV_THRIVEGROW \leq 2$	1.7%	2.42	Not reached	32.0%

The estimated probability of very low academic satisfaction reached 25% at $z = 1.80$ and 50% at $z = 2.26$. For intention to remain, the corresponding values were $z = 1.97$ and $z = 2.48$. The estimated probability of very low wellbeing reached 25% at $z = 2.42$ but did not reach 50% within the observed 1st–99th percentile climate range (Figure 5).

The risk curves therefore do not support a single general threshold at 2.5 SD for all outcomes. Instead, they identify outcome-specific probability reference points ranging from 1.80 to 2.42 SD for a 25% estimated risk. The results are most appropriately interpreted as exploratory institutional monitoring information requiring replication and prospective validation.

**Figure 5.** *Cont.*

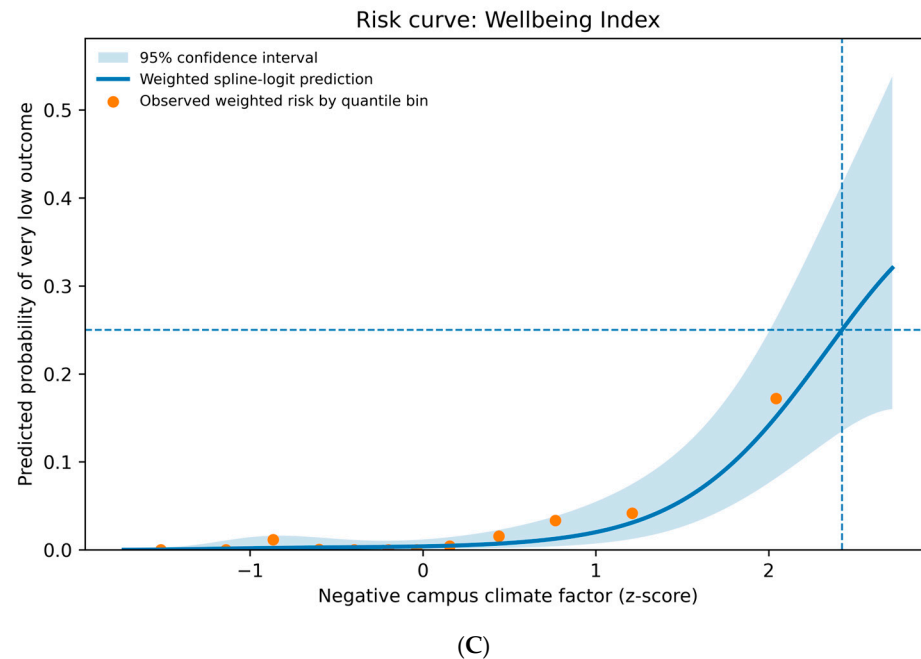


Figure 5. Context-specific risk curves for very low student outcomes across the observed negative climate distribution. (A) Academic satisfaction ≤ 2 ; (B) intention to remain ≤ 2 ; and (C) psychological wellbeing ≤ 2 . Solid lines are survey-weighted spline-logit estimates, shaded areas are 95% confidence intervals, and points represent observed weighted risks within climate quantile bins. Horizontal and vertical reference lines identify probability levels reached within the observed 1st–99th percentile range. These values are descriptive, institution- and period-specific reference points rather than validated universal intervention thresholds.

5. Discussion

5.1. Theoretical Contribution: Campus Climate as an Institutional Risk Indicator

The principal finding is that negative campus climate is strongly and consistently associated with academic satisfaction, intention to remain, and psychological wellbeing. The pattern appeared in weighted tertile comparisons, IPW and AIPW contrasts, continuous models, cutoff sensitivity analyses, and exploratory climate profiles. This convergence supports the interpretation of campus climate as an institutional-experience risk indicator rather than merely a descriptive diversity measure.

The original-scale estimates provide the most direct substantive interpretation. Students classified in the high-negative-climate group differed by approximately 0.73 points in academic satisfaction, 0.75 points in intention to remain, and 0.66 points in wellbeing on five-point scales after adjustment for the observed public-file covariates. The corresponding standardized contrasts were close to one outcome standard deviation. These are large adjusted differences, although their magnitude should not be interpreted as an experimentally identified effect.

The continuous models further indicate that the relationship is graded rather than confined to one arbitrary dichotomy. Each one-standard-deviation increase in negative climate was associated with declines of 0.764 SD in academic satisfaction, 0.725 SD in intention to remain, and 0.661 SD in wellbeing. Associations also became more adverse under more stringent high-climate cutoffs. The consistency between theoretical and empirical percentile definitions reduces concern that the sensitivity pattern resulted solely from arbitrary threshold selection.

These findings extend the diverse learning environment framework by linking institutional climate to a risk-monitoring perspective. Institutional structures and practices become educationally consequential through the signals students receive regarding fairness,

inclusion, communication, and recognition (Hurtado et al., 2012). The findings do not imply that student perceptions provide an error-free measurement of institutional conditions. They indicate that these perceptions contain systematic information strongly related to central dimensions of student experience.

The profile analysis reinforces this interpretation. Although the two-cluster solution produced stronger internal separation, the three-profile solution was more stable on average across bootstrap samples and distinguished positive, intermediate, and negative climate configurations. The approximately 1.3-point difference in satisfaction and intention to remain between the positive and negative profiles is educationally meaningful.

5.2. Wellbeing as a Plausible Explanatory Pathway

Psychological wellbeing statistically accounted for 21.4% of the association between negative climate and academic satisfaction and 19.3% of the association with intention to remain. This finding is consistent with the proposition that institutional climate becomes academically consequential partly through students' capacity to thrive within the university.

Negative perceptions of fairness, inclusion, or institutional communication may correspond with stress, reduced security, or diminished institutional trust. Lower wellbeing may then coexist with weaker satisfaction and less willingness to remain. This interpretation is consistent with research connecting campus climate, belonging, and mental health among university students, particularly among populations exposed to discrimination or marginalization (Huang & Fan, 2024; McField et al., 2025; McKenzie et al., 2024).

The mediation was partial. Most of the total association was not statistically accounted for by wellbeing, suggesting that other pathways may be relevant. These could include belonging, perceived discrimination, institutional trust, academic engagement, self-efficacy, and social integration. Future longitudinal studies should examine these pathways simultaneously and establish temporal ordering.

The cross-sectional design is especially important here. It is possible that negative climate contributed to lower wellbeing, that lower wellbeing influenced students' climate evaluations, or that both reflected unmeasured experiences.

This distinction also affects institutional implications. Wellbeing services may be valuable, but individual support cannot substitute for addressing institutional practices perceived as unfair or exclusionary. Conversely, climate improvement initiatives should not be assumed to replace mental health services. The findings support an integrated approach in which institutional climate, belonging, and wellbeing are treated as interconnected dimensions of student support.

5.3. Implications for Institutional Monitoring

The study also demonstrates how campus climate data can be translated into nonlinear probability information. The estimated probability of very low academic satisfaction reached 25% at $z = 1.80$, whereas the corresponding points were $z = 1.97$ for intention to remain and $z = 2.42$ for wellbeing. A 50% estimated probability was reached only for academic satisfaction and intention to remain, not for wellbeing.

These values should not be interpreted as universal early-warning thresholds. They were estimated from one institution, one survey period, and a cross-sectional sample. They were not evaluated prospectively, externally calibrated, or linked to tested interventions. Confidence intervals also widened substantially in the extreme climate tail.

The most defensible practical interpretation is therefore aggregate and exploratory. An institution could examine whether particular programs, cohorts, or student populations contain unusually high proportions of negative climate scores, provided appropriate privacy and minimum-cell protections are applied. Such information could prompt closer

qualitative investigation, climate dialog, or structural review. It should not automatically classify individual students or trigger punitive or stigmatizing actions.

This caution is consistent with the wider learning analytics literature, which distinguishes the technical ability to estimate risk from the institutional ability to intervene effectively and ethically. Systematic reviews have emphasized the need for external validation, transparent intervention protocols, and evidence that analytics-driven actions actually improve student outcomes (Larrabee Sønderlund et al., 2019; Ifenthaler & Yau, 2020).

Climate-informed analytics could nevertheless enrich conventional student-success systems. Grades and assessment data indicate academic performance; digital activity indicates engagement; wellbeing measures indicate psychological functioning; and climate measures indicate institutional experience. Integrating these sources may provide a more complete understanding of student vulnerability while reducing the tendency to locate risk exclusively within the student.

5.4. Limitations, Generalizability, and Future Research

Several limitations qualify the conclusions. First, the cross-sectional design precludes temporal ordering. Negative climate may contribute to lower satisfaction and wellbeing, but students with lower satisfaction or wellbeing may also perceive climate more negatively. Unmeasured common causes may influence both.

Second, exposure and outcomes were measured through the same survey. Common-method variance, response style, current affect, and social desirability could increase observed associations. The strong estimates should therefore not be interpreted as pure effects of objective institutional conditions.

Third, the masking of race/ethnicity is a particularly important limitation. Previous research demonstrates that campus climate experiences can differ across racial, ethnic, gender, disability, international student, and sexual orientation groups. The present study could not determine whether the overall estimates concealed more severe patterns within specific minoritized populations or intersections of identity.

Fourth, the findings come from one large public research university in the United States. The University of Michigan has institutional resources, governance arrangements, academic structures, and a DEI context that may differ from those of community colleges, private institutions, teaching-focused universities, or higher education systems outside the United States. The effect sizes, profiles, and probability reference points should not be generalized without replication.

Fifth, the survey was administered in 2016, before the COVID-19 pandemic. Since 2020, remote and hybrid learning, patterns of social interaction, mental health needs, institutional communication, and expectations of inclusion have changed substantially. The probability reference points estimated here cannot be assumed to remain stable in contemporary post-pandemic cohorts.

Finally, the risk models were descriptive rather than operational prediction models. They lacked temporal validation, out-of-sample calibration, decision-curve analysis, fairness evaluation, and intervention testing. Future research should use longitudinal, multi-institutional data to determine whether climate scores predict later changes in satisfaction, wellbeing, retention, or completion. Restricted-use data would permit intersectional and unit-level analysis, while repeated climate surveys could determine whether institutional improvements precede changes in student outcomes.

6. Conclusions

This study positions negative campus climate as an institutional-experience risk indicator associated with academic satisfaction, intention to remain, and psychological wellbeing.

Across weighted descriptive comparisons, cross-fitted AIPW contrasts, continuous models, and exploratory profiles, more negative perceptions of fairness, inclusion, communication, and general climate corresponded with substantially less favorable student outcomes.

The theoretical contribution lies in connecting the diverse learning environment framework with institutional analytics. Campus climate is not treated solely as an attitudinal diversity measure or as a fixed attribute of individual students. It represents students' interpretation of institutional conditions that may support or undermine academic and psychological integration. Statistical mediation further indicates that wellbeing is one plausible pathway through which climate is related to academic satisfaction and intention to remain, although most of the association remains attributable to other measured or unmeasured pathways.

The risk curves provide outcome-specific, context-dependent probability reference points rather than universal early-warning thresholds. They illustrate a potential role for climate surveys in aggregate institutional monitoring, but they do not justify automated classification or individual-level intervention without prospective validation, calibration, fairness assessment, and evidence of intervention effectiveness.

The conclusions remain limited by the cross-sectional design, shared self-report measurement, restricted covariate set, complete-case selection, masked race/ethnicity and institutional-unit variables, single-institution setting, and prepandemic data collection. Replication with longitudinal, multi-institutional, and post-pandemic data is required before the reported magnitudes, profiles, or risk reference points can be transferred to other higher education settings.

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Institutional Review Board Statement: Ethical review and approval were waived for this study because it was based exclusively on secondary analysis of publicly available, de-identified survey microdata from the University of Michigan Campus Climate Survey on Diversity, Equity and Inclusion (ICPSR 37096). The authors did not collect data directly from human participants and had no access to identifiable personal information.

Informed Consent Statement: Not applicable. This study used publicly available, de-identified secondary data. The authors did not recruit participants, collect primary data or have access to identifiable information.

Data Availability Statement: The data analyzed in this study are publicly available from the Inter-university Consortium for Political and Social Research (ICPSR): University of Michigan Campus Climate Survey on Diversity, Equity and Inclusion, Ann Arbor, Michigan (ICPSR 37096), available at <https://doi.org/10.3886/ICPSR37096.v1>. No new primary data were created in this study.

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Abbreviations

The following abbreviations are used in this manuscript:

ATE	Average Treatment Effect
DEI	Diversity, Equity and Inclusion
DR	Doubly Robust
ICPSR	Inter-university Consortium for Political and Social Research
IPW	Inverse Probability Weighting
LOWESS	Locally Weighted Scatterplot Smoothing
SD	Standard Deviation
SMD	Standardized Mean Difference
WGT_STUD	Student Survey Weight

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