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Perceived Algorithmic Curation in Academic Feeds and Student Well-Being in Higher Education: The Sequential Roles of Upward Social Comparison and Academic Pressure

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Article

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Abstract

AI-driven academic content feeds are increasingly used in students' learning, yet the psychological mechanisms linking algorithmic curation to student well-being remain underexplored. This study examines how AI-curated academic social feeds (AICAF) relate to university students' well-being through technostress dimensions (techno-overload, techno-complexity, techno-invasion) and a social–evaluative pathway involving upward social comparison and academic pressure. Using a two-sample measurement-validation approach in Vietnam, the AICAF scale was refined via pilot EFA (Sample 1; n = 120) and validated in an independent main sample (Sample 2; n = 337). The hypothesized model was tested using covariance-based structural equation modeling (CB-SEM) with bias-corrected bootstrapped indirect effects (5,000 resamples). AICAF was positively associated with upward social comparison and all technostress dimensions, and upward social comparison significantly predicted academic pressure. While the direct association between academic pressure and well-being was not statistically significant at the .05 level, AICAF showed a significant negative indirect association with well-being through the sequential pathway of upward social comparison and academic pressure. The findings extend Social Comparison Theory to AI-curated academic feed contexts and suggest that social–evaluative mechanisms may be more salient than technostress for explaining well-being differences within the studied setting.

1. Introduction

Artificial intelligence (AI) is being incorporated into students' daily education through algorithmically selected knowledge streams. through algorithmically selected knowledge streams. Alongside formal learning management systems, students often engage with academic resources via feed-based platforms (e.g., video services, scholarly communities, and social media groups) where algorithms prioritize, recommend, and perpetually display content based on prior interactions (Gillespie, 2014; Zawacki-Richter et al., 2019). Previous studies have predominantly focused on instructional advantages like personalization and learning efficacy (Holmes et al., 2022; Zawacki-Richter et al., 2019), yet feed-based curation may also transform students' psychological experiences by offering constant exposure to performance-oriented stimuli and substantial information streams (Eppler & Mengis, 2004; Matthes et al., 2020). However, empirical research on AI in education primarily emphasizes instrumental outcomes (Bond et al., 2020), neglecting the effects on well-being and the psychological mechanisms associated with prolonged exposure to algorithmically generated academic content.

In recent years, students' access to academic content has increasingly taken place through platforms organized around content "feeds." Beyond traditional learning management systems, students are increasingly exposed to learning materials through AI-mediated environments such as video-sharing platforms, academic groups on social media, and online learning communities (Dabbagh & Kitsantas, 2012). These platforms do not simply function as stores of instructional content; instead, they actively curate and prioritize the information that students encounter every day. In contrast to conventional learning management systems, where instructional information is predominantly governed by educators

and presented inside a rigid framework, AI-curated academic feeds function via ongoing algorithmic ranking methods (Gillespie, 2014). The content appearing in students' feeds is organized based on behavioral signals such as interaction history, levels of engagement, and prior usage patterns. Consequently, the distribution of academic content in these environments is not neutral but dynamic and personalized, while learners themselves are often unaware of how the underlying algorithms operate. This algorithmic steering mechanism transforms academic feeds into a distinctive cognitive environment, in which students are continuously exposed to learning content in a largely passive and difficult-to-control manner. Students frequently encounter academic resources that they did not actively seek, alongside associated social signals such as popularity metrics, engagement statistics, or implicit cues for social comparison (Eppler & Mengis, 2004; Matthes et al., 2020). Thus, AI-curated academic feeds constitute a learning environment that significantly diverges from traditional educational institutions, underscoring the need for more investigation into the effects of such settings on students.

Despite the growing prevalence of AI-curated academic social feeds as a learning environment, existing research has insufficiently clarified the psychological mechanisms via which these settings influence students' mental well-being. Prior studies on AI in education have primarily focused on learning outcomes or general perceptions, whereas the psychological impacts of prolonged exposure to algorithmically curated academic content remain inadequately explored (Zawacki-Richter et al., 2019). Two recognized theoretical frameworks, technostress and social comparison, provide essential insights for comprehending these consequences; nonetheless, they have not been extensively utilized in this context. Studies on technostress suggest that information technology might induce stress as a result of information overload, system complexity, and persistent technological disruption (Tarafdar et al., 2019). Social comparison theory elucidates how awareness of others' accomplishments affects self-assessment, perceived pressure, and emotional states (Festinger, 1954) However, these frameworks have typically been developed and assessed independently and are rarely examined as simultaneous psychological mechanisms inside the same digital context (Verduyn et al., 2017). Moreover, despite their theoretical importance, technostress and social comparison have not been systematically employed in AI-generated academic feeds (Ragu-Nathan et al., 2008). Unlike traditional information technologies or previously analyzed social media platforms, AI-curated academic feeds enable continuous information distribution, algorithmic prioritization, and integrated social signals, creating a hybrid technological-social environment that may simultaneously induce stress and comparison mechanisms (Holmes et al., 2022). Theoretical and contextual shortcomings are intensified by methodological limitations, as few research employs covariance-based structural equation modeling (CB-SEM) to investigate various psychological pathways within a unified framework (Kline, 2016). The distinct and simultaneous effects of technostress and social comparison on student well-being in AI-enhanced learning environments have not been sufficiently examined using appropriate analytical techniques(Hayes, 2018).

This study seeks to elucidate the impact of AI-curated academic social feeds on students' mental well-being by examining specific psychological mechanisms, which addresses the stated theoretical, contextual, and methodological deficiencies. The study specifically investigates how exposure to AI-driven academic feeds triggers technostress reactions and social-cognitive comparison processes as

distinct yet concurrent psychological pathways, influencing students' well-being. This study seeks to elucidate the simultaneous influences of technostress and social comparison on students' psychological experiences in algorithmically regulated learning environments.

This research enhances theoretical and practical understanding in the fields of artificial intelligence in education and student mental health. It theoretically advances AI-in-education research by perceiving AI-curated academic social feeds not merely as material delivery systems, but as learning environments with distinct psychological impacts on learners. This perspective expands existing research to include the well-being implications of algorithmically mediated learning settings, alongside instructional effectiveness. The research integrates technostress and social comparison into a unified, theory-based associative model, demonstrating how AI-generated academic feeds influence students' mental health through simultaneous psychological mechanisms. Simultaneously examining these mechanisms elucidates the unique yet concurrent functions of technology-induced stress and social-cognitive comparison processes in digital learning contexts. Third, by presenting empirical evidence from Vietnam —a non-Western setting that is underrepresented in research on AI, algorithms, and well-being—the study augments the contextual sensitivity and cross-cultural applicability of current theoretical frameworks. The findings provide practical implications for universities and providers of digital learning platforms. Identifying technostress pathways can guide the development of recommendation systems that manage information exposure, alleviate cognitive overload, and foster healthier learning patterns. Insights into social comparison mechanisms can assist educators and platform managers in identifying early indicators of academic strain and executing prompt interventions to protect students' mental well-being in AI-driven learning settings.

This study is guided by the following research question:

Through which distinct psychological mechanisms do AI-curated academic content feeds influence students’ mental well-being, particularly via technostress and upward social comparison?

2. Literature Review

2.1 Technostress in AI-Curated Academic Feed–Based Learning Environments

Within AI-curated academic feeds, students rarely encounter content in a purely self-directed way. Students do not encounter academic content in these feeds by chance. Certain articles, peer achievements, or recommended readings keep reappearing, while others quietly drop out of sight. The logic behind this ordering is not always clear to the learner. After a while, exposure becomes patterned rather than intentional. Students find themselves seeing particular kinds of academic material again and again, even when they did not explicitly choose to look for it (Beyens et al., 2021; Zawacki-Richter et al., 2019). Traditional learning platforms operate differently. Students typically decide when to log in, which materials to access, and how long to remain engaged. By contrast, academic feeds continue to update

even when learners are not actively searching for content, subtly shaping what appears before them. Content appears continuously, shaping what students see and how often they see it. As a result, learning materials become woven into daily routines in a way that is harder to control.

Within this context, prolonged interaction with algorithmically coordinated learning systems may activate technostress responses, reflecting psychological strain arising from the ways in which technology structures the pace, organization, and boundaries of daily learning activities.

Due to the continuously and often in dense feeds content clusters, AI-curated academic feeds can create conditions called techno-overload, whereby students are required to process large volumes. New readings appear, updates arrive quickly, and highlighted materials accumulate within short time spans. The experience is less about choosing what to study and more about trying to keep up. This pattern resembles what Tarafdar et al., (2007) and Karr-Wisniewski & Lu (2010) refer to this experience as techno-overload, which occurs when technological systems confront users with more information, and at a faster pace, than they can realistically process.

Beyond techno-overload, the complexity of these recommendation systems also deserves attention. The algorithms behind them are usually obscure, and students rarely realize why certain materials are prioritized while others are not. As a result, students may find themselves repeatedly adapting their behavior, experimenting with different patterns of engagement in an attempt to remain in step with the content that the system prioritizes. Over time, this repeated effort to understand and adapt can increase cognitive strain. Ragu-Nathan et al., (2008) and Tarafdar et al., (2019) describe a similar condition as techno-complexity, referring to stress that emerges when technology becomes so intricate that users struggle to manage it comfortably.

In addition to pressures related to volume and complexity, the continuous algorithmic intervention in academic content exposure may also erode personal boundaries, as students perceive learning activities to intrude into their time, space, and sense of autonomy. Such experiences are called techno-invasion, which has been empirically established as a dimension of technostress associated with perceived loss of control and the encroachment of technology into individuals' personal lives (Ayyagari et al., 2011; Tarafdar et al., 2015). Taken together, these mechanisms suggest that within AI-curated academic feed environments, where learning content is algorithmically structured, continuously distributed, and only partially regulated by users, technostress has a clear theoretical basis as a potential psychological response emerging from the technological reconfiguration of students' everyday learning experiences.

H1a

AI-curated academic feeds (AICAF) is positively associated with techno-overload (TOL).

H1b

AI-curated academic feeds (AICAF) is positively associated with techno-complexity (TOC).

H1c

AI-curated academic feeds (AICAF) is positively associated with techno-invasion (TIV).

2.2 Technostress and Student Well-Being

Technostress has been referred to as a form of prolonged psychological strain that stems from sustained interactions with technological systems in academic and work-related contexts. From a stress–strain perspective, long-term pressure gradually drains core psychological resources, thereby contributing to declines in individual well-being ((Hobfoll, 1989; Lazarus & Folkman, 1984) When technostress persists over time, people may become emotionally and psychologically drained, often expressed as emotional exhaustion, psychological fatigue, and mental weariness. Findings in the technostress literature point to a similar pattern: as strain builds, resilience tends to erode. Individuals may struggle to sustain emotional balance when technological pressures remain constant (Ragu-Nathan et al., 2008; Tarafdar et al., 2015).

As internal resources decline, people may begin to feel less energized and less emotionally balanced. Their ability to maintain positive affect can weaken, and everyday activities may be less effective. Comparable findings have been reported in studies on the psychological consequences of technostress (Ayyagari et al., 2011; Tarafdar et al., 2011)).

Over time, emotional exhaustion and reduced functioning may gradually shape overall well-being. Students exposed to sustained technostress often report poorer mental health and lower life satisfaction (Brooks & Califf, 2017; Maier et al., 2015). It is therefore more accurate to view technostress not as a temporary reaction, but as a continuing source of psychological pressure that can carry longer-term consequences.

H2a

Techno-overload (TO) is negatively associated with well-being (WB).

H2b

Techno-complexity (TC) is negatively associated with well-being (WB).

H2c

Techno-invasion (TI) is negatively associated with well-being (WB).

2.3 The Mediating Role of Technostress between AI-Curated Academic Feeds and Well-Being

To investigate the association between AI-curated academic feeds and well-being, the study view technostress as a possible mediator. From this perspective, online learning environments may influence students' psychological states indirectly, through the strain that builds up from continued interaction with technological systems.

Within stress–strain frameworks, pressure does not tend to influence well-being directly. Their influences typically operate through a gradual build-up of psychological strain, which links contextual conditions to psychological outcomes (Hobfoll, 1989; Lazarus & Folkman, 1984).

In technology-mediated learning environments, operational conditions characterized by continuity and prolonged exposure have been identified as sources of psychological strain, thereby reinforcing the role of technostress as an intermediate strain response linking technological contexts to learners' psychological experiences (Ragu-Nathan et al., 2008; Tarafdar et al., 2015).

At the same time, research on sustained psychological strain indicates that such accumulated stress states tend to undermine well-being through cumulative psychological consequences over time (Ayyagari et al., 2011; Brooks & Califf, 2017).

Integrating these two ways of reasoning suggests that the impact of AI-curated academic feeds on well-being does not tend to occur directly, but is instead may cause through technostress, thereby supporting its mediating role in this relationship. Accordingly, techno-overload, techno-complexity, and techno-invasion are examined as potential mediating mechanisms linking AI-curated academic feeds to students' well-being.

H3a

Techno-overload (TO) mediates the association between AI-curated academic feeds and students' well-being.

H3b

Techno-complexity (TC) mediates the association between AI-curated academic feeds and students' well-being.

H3c

Techno-invasion (TI) mediates the association between AI-curated academic feeds and students' well-being.

2.4 AI-Curated Academic Feeds and Upward Social Comparison

In AI-curated academic feed-based learning environments, algorithms determine which academic content becomes more visible to students. At the same time, peers' learning activities and achievements tend to be more remarkable (Cotter, 2019).

Consistent exposure to information regarding peers' academic achievements creates significant comparison standards, encouraging students to evaluate their own academic standing in relation to others in their surroundings(D'Angelo & Toma, 2017; Gerber et al., 2018). Social Comparison Theory asserts that individuals have an inherent tendency to evaluate themselves by comparing their accomplishments and development with those of others, particularly in contexts where peer information is prominently presented and easily accessible (Festinger, 1954).

In esteemed educational environments, students often rely on the achievements and progress of their reference groups as benchmarks for evaluating their relative academic standing. When algorithmically highlighted information predominantly features high-achieving individuals, this evaluative process tends to result in upward social comparison, as learners continually measure themselves against superior academic standards in their environment(Buunk & Gibbons, 2007; Gerber et al., 2018).

In AI-curated academic feeds, the repeated existence of academic content makes high achievement standards more visible, increasing the likelihood that students compare themselves with higher-performing peers.

H4

AI-curated academic feeds are positively associated with upward social comparison.

2.5 Upward Social Comparison and Academic Pressure

Upward social comparison refers to the tendency when students evaluate their academic standing by looking to peers who seem to be performing at a higher level. Such comparisons provide a comparison standard for judging one's own performance within the same learning context.

Through upward social comparison, students become more aware of their academic expectations and the gap between them with others. As they compare themselves against higher-performing peers, the difference between their own abilities and others becomes more remarkable. Thus, they begin to ask what level of achievement is necessary to keep up.

Social Comparison Theory and its extensions regarding self-evaluation and gaps posit that comparing oneself to higher-performing individuals is crucial for goal-oriented performance assessment, therefore supporting the establishment of perceived academic demands and expectations (Buunk & Gibbons, 2007; Festinger, 1954).

In competitive and performance-oriented learning environments, self-assessment through upward social comparison often correlates with heightened perceptions of academic pressures, as students perceive a

necessity to meet, sustain, or match prominent performance benchmarks. In this context, academic pressure is defined as the perceived obligation to exhibit academic proficiency and results aligned with established standards, indicating evaluative performance pressure rather than acute psychological stress responses (Putwain, 2007).

Upward social comparison increases the prominence of high academic standards and amplifies awareness of performance gaps, likely triggering academic pressure by internalizing achievement-related expectations and norms within the educational context.

H5

Upward social comparison has a positive association on academic pressure.

2.6 Academic Pressure and Student Well-Being

Academic pressure can be understood as the way students perceive performance-related demands and expectations, especially when they feel compelled to meet established academic standards (Putwain, 2007).

From achievement-related and evaluative pressure perspectives, prolonged exposure to performance expectations can undermine positive psychological states, particularly when perceived academic demands persist over time (Salmela-Aro & Upadyaya, 2014).

Academic pressure may give rise to evaluative emotional responses, whereby students frequently experience concern, mild emotional tension, and feelings of insecurity related to meeting academic expectations (Pascoe et al., 2020). These responses reflect heightened emotional sensitivity to achievement standards and performance demands, rather than states of emotional exhaustion or psychological burnout (Lazarus & Folkman, 1984).

These evaluative emotional responses may gradually undermine both psychological functioning and motivation. Students may report lower levels of satisfaction and find it increasingly difficult to maintain emotional balance, which in turn can reduce their engagement in learning activities (Salanova et al., 2010).

Over time, emotional strain and reduced functioning may appear, contributing to overall declines in well-being. Students suffer from academic pressure often report poorer mental health and lower life satisfaction than those who do not (Dyrbye et al., 2006).

Taken together, academic pressure should not be considered merely a situational perception of academic demands, but as a condition with the potential to exert negative effects on students' well-being through cumulative emotional and psychological consequences over time ((Levecque et al., 2017).

H6

Academic pressure is expected to be negatively associated with students' well-being.

2.7 The Mediating Role of Academic Pressure between Upward Social Comparison and Well-Being

The link between upward social comparison and well-being is unlikely to be direct. Academic pressure may help explain how comparison-based learning experiences shape students' psychological outcomes.

Social Comparison Theory, along with its later developments on self-evaluation and discrepancy, proposes that individuals assess themselves by looking to higher-performing others (Buunk & Gibbons, 2007; Festinger, 1954). In doing so, they become more aware of where they stand and how far they fall short of visible standards. These perceived gaps can gradually intensify expectations and perceived academic demands. For this reason, the effects of social comparison on well-being are unlikely to be immediate; they are more plausibly carried through academic pressure.

In competitive learning environments, upward comparison tends to sharpen attention to achievement norms and performance differences. As students become increasingly conscious of these standards, the sense of obligation to meet them may (Festinger, 1954; Gerber et al., 2018; Putwain, 2007).

Prior research indicates that sustained academic pressure is associated with declines in well-being. Continued exposure to performance-related demands has been linked to poorer psychological health over time (Liu & Lu, 2011; Quach et al., 2015).

H7

Academic pressure mediates the relationship between upward social comparison and students' well-being.

2.8 A Serial Mediation Model Linking AI-Curated Academic Feeds and Student Well-Being

In addition, this study considers a sequential process whereby AI-curated academic feeds affect well-being through upward social comparison and subsequent academic pressure.

Within AI-curated academic feed environments, algorithms do more than simply display content. By highlighting certain achievements or materials repeatedly, they increase students' exposure to visible academic standards, which can in turn trigger comparison-based self-evaluation (Festinger, 1954; Gerber et al., 2018).

When upward social comparison draws attention to high performance standards, students may become increasingly aware of the gap between their own performance and others. This awareness can strengthen the need to meet the established standards, thereby increasing academic pressure (Buunk & Gibbons, 2007; Putwain, 2007).

Academic pressure may be associated with lower well-being through cumulative evaluative experiences related to perceived academic demands, consistent with prior research linking achievement-related expectations to reduced psychological well-being (Liu & Lu, 2011).

Integrating these associations suggests that AI-curated academic feeds are theorized to influence well-being indirectly through a sequential process that begins with upward social comparison, proceeds to academic pressure, and ultimately contributes to diminished student well-being.

H8

AI-curated academic feeds are indirectly associated with students' well-being through a serial mediation process involving upward social comparison and academic pressure.

Collectively, the hypotheses articulate two distinct yet complementary mechanisms linking AI-curated academic feeds to student well-being: a cognitive-technological strain pathway (via technostress dimensions) and a social-evaluative pathway (via upward social comparison and academic pressure). The integrated structural model is presented in Fig. 1.

3. Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional, and theory-driven (explanatory) research design. Data collection involved two independent samples: a pilot sample for exploratory scale refinement and a separate main sample for CFA and structural model testing. Both samples were collected as cross-sectional surveys. This design was selected to test theoretically specified relationships among the study variables, rather than to provide descriptive accounts or conduct open-ended exploration. The core constructs of interest, AI-curated academic feeds, technostress, upward social comparison, and well-being, represent students' subjective perceptions, lived experiences, and psychological states. These constructs are not directly observable through overt behavior nor can they be objectively captured through system-level data. Accordingly, a perception-based quantitative approach is appropriate for capturing the underlying nature of the phenomena under investigation.

Data were collected using a self-administered questionnaire with Likert-type scales. This approach enables the quantification of respondents' perceived experiences of abstract psychological constructs and facilitates the examination of both measurement structures and structural relationships through latent variable modeling. Such an approach is well established in psychological, educational, and technology-related behavioral research.

With respect to inferential goals, the study is oriented toward mechanism-based inference. All mediation paths are interpreted as theory-consistent associative mechanisms rather than causal processes. These mechanisms are interpreted as theoretically informed associative processes rather than causal

mechanisms. Rather than merely assessing whether AI-curated academic feeds are associated with students' well-being, the analysis focuses on elucidating the psychological pathways through which such effects occur, specifically via technostress and upward social comparison. In doing so, the study also examines whether these mechanisms operate in parallel or differentially in explaining how AI-mediated learning environments shape students' well-being. This analytical focus enables the testing of mediation models that contribute to a deeper theoretical understanding of psychological processes in AI-driven learning contexts, moving beyond surface-level associations.

Given the cross-sectional nature of the design, mediation effects are interpreted as theory-consistent indirect effects rather than evidence of temporal or causal relationships. Accordingly, the study aims to evaluate a theoretically grounded explanatory model rather than to establish causal claims over time.

3.2 Population and Sampling

Population

The target population of this study consists of undergraduate students who engage in learning activities involving digital platforms, including social media, online learning platforms, or academic content distribution systems with recommendation features. This group of learners is frequently exposed to academic content streams that are selected, organized, or suggested by intelligent technological systems, in which AI plays an increasingly prominent role.

The selection of undergraduate students as the study population is appropriate because they are directly and continuously influenced by AI-driven digital learning environments. Moreover, students' well-being in academic contexts is not only of practical relevance to educational quality and learner experience, but also of theoretical significance for advancing understanding of the psychological mechanisms emerging from human–technology interactions in higher education.

Sampling

This study employed a non-probability sampling approach, specifically combining convenience sampling and purposive sampling. The inclusion criteria were as follows: (i) being an undergraduate student; (ii) having been exposed, within the past three months, to at least one platform involving algorithmic recommendation or academic content distribution (e.g., social media, learning management systems, or online learning platforms); and (iii) having completed the questionnaire in full.

This sampling strategy was adopted due to the difficulty of establishing a comprehensive and clearly defined sampling frame for the target population, particularly given the diversity in how students access and engage with digital learning platforms and social media.

In addition, the primary objective of the study was to test a theoretical model and examine the psychological mechanisms linking the study variables, rather than to statistically generalize the findings to the entire student population. As such, a non-probability sampling approach is considered appropriate

and commonly employed in behavioral, psychological, and educational research utilizing Structural Equation Modeling (SEM), where the emphasis lies on evaluating relationships among theoretical constructs rather than estimating population parameters.

The target sample size was determined a priori based on methodological recommendations for covariance-based SEM (CB-SEM), with particular emphasis on estimation stability and mediation testing in models with multiple latent variables. Given the sensitivity of CB-SEM to sample size and covariance matrix stability, the study targeted a main sample exceeding 300 cases to ensure reliable model fit estimation and adequate power for detecting small-to-moderate indirect effects.

3.3 Measurement

A five-point Likert scale was employed to measure the psychological constructs in the research model. This scale was selected to balance measurement resolution and respondents' cognitive load, making it particularly suitable for student samples and surveys of moderate length. In addition, five-point Likert scales are more likely to yield stable response distributions, which is appropriate for SEM-based analyses oriented toward theory testing.

3.4 Constructs specification

Prior to conducting the analyses, the study explicitly specified the measurement logic of each construct, distinguishing between reflective constructs and constructs requiring exploratory validation, in order to ensure conceptual consistency between theory and the measurement model.

The components of technostress, namely techno-overload, techno-complexity, and techno-invasion, were specified as three reflective constructs. Each dimension captures a specific manifestation of technology-related strain experienced by students in digital learning environments, reflecting different stress-inducing aspects of technology use rather than interchangeable indicators of a single unitary construct. Accordingly, these dimensions were modeled separately to allow for differential effects across the structural paths.

Similarly, upward social comparison, academic pressure, and well-being were conceptualized as latent psychological states in which the observed indicators are relatively interchangeable, and were therefore specified as reflective constructs.

In contrast to approaches that conceptualize technostress as a higher-order construct, the present study adopts a multidimensional specification in which techno-overload, techno-complexity, and techno-invasion are treated as parallel first-order constructs. This modeling strategy is consistent with empirical evidence suggesting that different dimensions of technostress may operate independently and exert distinct psychological effects, particularly in contemporary AI-mediated learning contexts.

3.5 AI-Curated Academic Feeds

Unlike the other constructs in the model, AICAF is highly context-dependent and is intended to capture an AI-mediated academic information environment rather than mere technology usage intensity. In this study, AICAF is conceptualized as students' aggregated perceptions of an AI-coordinated learning environment, rather than as objective exposure frequency or self-reported technology use. Although the initial conceptualization of AICAF was informed by three theoretical domains of AI-driven algorithmic curation, the study did not impose a priori assumptions that the measurement indicators would map precisely onto these domains in the empirical data.

Accordingly, exploratory factor analysis (EFA) was employed for AICAF as a theory–measurement calibration step, aimed at assessing the degree of alignment between the proposed conceptual structure and the way indicators empirically clustered within the study context. The purpose of the EFA was not to generate new theory, but to refine the correspondence between the conceptual framework and the empirical measurement structure of a construct characterized by contextual and conceptual complexity. This construct captures perceived algorithmic structuring of academic content rather than general digital engagement or platform usage behavior.

Following a two-step validation procedure, EFA was conducted on the Wave 1 sample to explore the latent factor structure of AICAF. Subsequently, confirmatory factor analysis (CFA) was performed on an independent Wave 2 sample to cross-validate and confirm the identified structure prior to its inclusion in the structural model.

Importantly, this construct explicitly excludes usage frequency or duration, focusing solely on perceived algorithmic structuring. Instead, it reflects students' perceived exposure to algorithmically curated academic content streams, emphasizing the structuring role of AI-driven prioritization rather than individual usage intensity.

3.6 Measurement Scale Development and Refinement

Measurement scales for technostress, upward social comparison, academic pressure, and well-being were adapted from established prior studies and contextually adjusted to fit digital learning environments. In contrast, AICAF was developed using an initial pool of ten indicators derived from three theoretical domains of AI-driven algorithmic curation. Particular attention was paid during item development to avoid conceptual drift toward general social media usage behaviors.

Pilot testing was conducted to identify semantic ambiguity, potential construct contamination, and inconsistent response patterns, issues that are especially critical for a context-sensitive construct such as AICAF. Prior to the two main waves of data collection, the scales underwent content review and semantic refinement through a small pilot study aimed at detecting unclear wording and risks of construct overlap. All revisions were strictly linguistic in nature and did not alter the underlying conceptual meaning of the measurement scales.

3.7 Measurement Evaluation Criteria and SEM Analytical Approach

Given the theory-testing orientation of the study, measurement model analyses were conducted using covariance-based structural equation modeling (CB-SEM). The reliability and validity of the measurement scales were assessed through internal consistency reliability, convergent validity, and discriminant validity to ensure that the constructs were measured in a stable and conceptually distinct manner prior to testing the structural relationships and mediation mechanisms in the research model.

Discriminant validity was primarily evaluated using the heterotrait–monotrait (HTMT) ratio. The Fornell–Larcker criterion and latent variable correlations were reported as supplementary checks to strengthen the robustness of conclusions regarding discriminant validity. Where necessary, additional tests were conducted for construct pairs exhibiting high correlations by comparing a constrained model, in which the correlation between two constructs was fixed to one, with an unconstrained model using chi-square difference testing, thereby providing further support for discriminant validity.

3.8 Data Screening

Missing data

The dataset was examined for both the extent and pattern of missing values prior to analysis. Inspection of the final dataset indicated that no missing data were present across the observed variables; therefore, no missing data treatment was required for subsequent SEM analyses. This preliminary check was conducted to ensure that the estimation results were not affected by incomplete responses, which can bias parameter estimates and violate key assumptions in SEM when left uncontrolled.

Outliers

Both univariate and multivariate outliers were examined to identify observations with atypical response patterns. As outliers have the potential to distort the covariance matrix and bias parameter estimates in SEM, such cases were carefully reviewed. Decisions regarding the retention or removal of outliers were not based solely on statistical criteria, but also considered the substantive plausibility and contextual consistency of respondents' answers.

Distribution checks

The distributional characteristics of the observed variables were assessed using descriptive indices, including skewness and kurtosis. The purpose of this step was not to enforce strict normality assumptions, but to understand the empirical distribution of the data prior to further analyses. This examination helped ensure appropriate interpretation of results, particularly given the relative robustness of SEM to moderate deviations from normality.

Common Method Bias

Because all data were collected from a single source at one point in time, both procedural remedies and statistical diagnostics were employed to address the potential risk of common method bias. At the procedural level, the survey was designed to minimize item ambiguity and reduce evaluation

apprehension among respondents. At the statistical level, Harman's single-factor test was conducted as an initial diagnostic, and a common latent factor (CLF) was incorporated into the CFA to assess the magnitude of common method variance.

Response Logic Checks

Response quality was evaluated using multiple indicators, including survey completion time, straight-lining patterns (e.g., identical responses across all items), and indicators of inattentive responding.

Of the initial 358 collected responses, 21 cases (5.9%) were excluded at the data screening stage prior to SEM estimation, due to clear straight-lining behavior (e.g., consistently selecting the same scale point across all items, such as all "1" or all "5"), suggesting insufficient engagement with the questionnaire.

The final analytic sample therefore consisted of 337 valid responses, which were retained for subsequent SEM analyses to ensure data quality and reliability.

3.9 Analytical Strategy

The analytical strategy of this study was guided by a theory-testing orientation; accordingly, covariance-based structural equation modeling (CB-SEM) was employed as the primary analytical method. CB-SEM enables the simultaneous assessment of the measurement model and the structural model and is particularly suitable for evaluating theoretically specified relationships among latent psychological constructs. This approach is well aligned with the study's objective of examining theoretically grounded associative pathways rather than maximizing predictive accuracy.

Structural Model Specification and Mediation Analysis

The relationships among latent constructs were examined through theoretically specified structural paths within the CB-SEM framework. To address the research questions concerning underlying psychological mechanisms, mediation analysis was conducted to evaluate indirect pathways linking AI-curated academic feeds to student well-being via technostress dimensions and upward social comparison. This approach allowed for the estimation of direct, indirect, and total effects within a single coherent analytical model.

Academic pressure was specified as a theoretically grounded mediating construct representing achievement-related evaluative demands that arise from social comparison processes in AI-curated learning environments. Conceptualizing academic pressure as a mediator, rather than as a control variable, enabled a clearer interpretation of how social–evaluative mechanisms transmit the influence of AI-curated academic feeds to students' well-being.

Given the non-normal distribution commonly observed in indirect effects, bias-corrected bootstrapping procedures with 5,000 resamples were employed to construct confidence intervals for mediation effects. This procedure enhanced the robustness of statistical inference and provided a more reliable basis for evaluating the significance of indirect pathways within the proposed associative model.

4. Result

4.1 Pilot EFA results for AICAF scale refinement

4.1.1 Assessment of Factorability

Before conducting the EFA, the suitability of the pilot dataset was examined. The Kaiser–Meyer–Olkin (KMO) value reached 0.910, indicating excellent sampling adequacy. Bartlett's test of sphericity was statistically significant, $\chi^2(45) = 650.849$, $p < .001$, confirming that the correlation matrix contained sufficient shared variance for factor extraction. These results supported proceeding with exploratory analysis.

4.1.2 Factor Extraction and Structural Evaluation

Exploratory factor analysis was performed using Principal Axis Factoring with Promax rotation to allow correlated latent dimensions. The initial solution yielded two eigenvalues above 1 (5.496 and 1.012), accounting for 56.18% of total variance.

Despite meeting the eigenvalue criterion, inspection of the scree plot revealed a clear inflection after the first factor. Examination of the loading matrix further indicated that only the first factor demonstrated strong loadings and conceptual interpretability. The second factor did not represent a coherent latent dimension. Accordingly, AICAF was retained as a unidimensional construct in the pilot stage.

4.1.3 Item Purification

Item refinement was guided by the loading structure. Item A8 loaded primarily on the minor secondary factor and did not contribute to the dominant latent dimension; it was therefore removed. Item A7 exhibited cross-loadings and lacked sufficient structural clarity for a single-factor solution, leading to its exclusion.

Following purification, six indicators remained. These items showed strong primary loadings and no substantive cross-loadings. The resulting scale demonstrated parsimony and structural consistency, supporting its use for subsequent confirmatory factor analysis in the main sample.

4.2 Overview of Participant Demographic Information

Table 1
Demographic Characteristics of the Respondents

Respondents' characteristics	Frequency	Percent
Gender		
Male	141	41.8%
Female	196	58.2%
Institution		
FPT University	179	53.1%
Can Tho University of Technology	64	19%
Can Tho University (CTU)	56	16.6%
Vietnam National University, Ho Chi Minh City (VNU-HCM)	16	4.7%
Ho Chi Minh City University of Education	14	4.2%
Ho Chi Minh City University of Technology (HCMUT)	8	2.4%
Academic year		
First year	75	22.3%
Second year	100	29.7%
Third year	88	26.1%
Fourth year	74	22.0%
Major		
Information Technology / Computer Science	41	12.2%
Social Sciences and Humanities	29	8.6%
Economics/ Business/ Finance	55	16.3%
Engineering and Technology (excluding IT)	96	28.5%
Language and Foreign Language Studies	57	16.9%
Education/ Pedagogy	42	12.5%
Medicine and Health Sciences	17	5.0%
Daily Time Spent on Digital Learning Platforms		
Less than 1 hour per day	33	9.8%
Approximately 1–3 hours per day	74	22.0%
Approximately 3–5 hours per day	106	31.5%

Respondents' characteristics	Frequency	Percent
Gender		
More than 5 hours per day	124	36.8%
Primary Mode of Learning		
Blended learning	109	32.3%
Face-to-face (offline)	57	16.9%
Online learning	171	50.7%

The final sample consisted of 337 undergraduate students from several universities in Vietnam. Female students accounted for 58.2% of the sample, while 41.8% were male. More than half of the respondents were enrolled at FPT University (53.1%), followed by students from Can Tho University of Technology (19.0%) and Can Tho University (16.6%), with smaller proportions from major universities in Ho Chi Minh City.

Most participants were in the early stages of their undergraduate programs, with 29.7% in the second year and 22.3% in the first year. The sample represented a wide range of academic disciplines, led by Engineering and Technology (28.5%), Language and Foreign Language Studies (16.9%), and Economics/Business/Finance (16.3%).

Regarding learning behaviors, a majority of students reported intensive use of digital learning platforms, with 68.3% spending more than 3 hours per day. Online learning was the dominant mode (50.7%), followed by blended learning (32.3%) and face-to-face learning (16.9%).

4.3 Measurement model assessment

4.3.1 Confirmatory Factor Analysis (CFA)

Table 4
Model Fit Indices for the Measurement Model

Model fit statistic	Result achieved	Recommended value
CMIN/DF	1.176	< 3.0
GFI	0.918	> 0.90
CFI	0.981	> 0.90
TLI	0.978	> 0.90
IFI	0.982	> 0.90
RMSEA	0.023	< 0.08

A confirmatory factor analysis (CFA) was conducted to evaluate the adequacy of the measurement model prior to structural model testing. The results indicated an excellent model fit ($\chi^2 = 386.978$, df = 329, $\chi^2/df = 1.176$). Incremental fit indices exceeded recommended thresholds (CFI = 0.981; TLI = 0.978), while the RMSEA value indicated a close fit to the data (RMSEA = 0.023, 90% CI [0.011, 0.032], PCLOSE = 1.000). Overall, these results confirm that the measurement model provides a sound basis for subsequent reliability, validity, and structural analyses.

4.3.2 Reliability and Descriptives

Table 2
Reliability and Convergent Validity

Construct	Items	Mean (range)	SD (range)	Std. loadings (range)	Cronbach's α	CR	AVE
AICAF	6	2.87–3.11	1.23–1.27	0.647–0.775	0.862	0.862	0.512
Technology Overload (TO)	3	2.88–3.05	1.20–1.27	0.598–0.722	0.718	0.719	0.463
Technological Complexity (TC)	3	2.82–2.99	1.24–1.30	0.655–0.793	0.774	0.776	0.537
Technological Invasion (TI)	3	2.83–2.90	1.20–1.24	0.671–0.730	0.743	0.743	0.491
Upward Social Comparison (USC)	4	2.94–3.05	1.23–1.28	0.696–0.765	0.812	0.813	0.521
Academic Pressure (AP)	4	2.88–2.96	1.17–1.29	0.666–0.779	0.804	0.805	0.509
Well-being (WB)	5	2.90–3.10	1.22–1.30	0.649–0.758	0.824	0.825	0.486

Table 2 presents the descriptive statistics and reliability assessment of the measurement model. Across constructs, mean values ranged from 2.82 to 3.11, indicating moderate levels of agreement among respondents. Standard deviations ranged from 1.17 to 1.30, reflecting adequate variability in responses.

All standardized factor loadings were statistically significant and exceeded the recommended threshold of 0.50, ranging from 0.598 to 0.793. These results indicate satisfactory indicator reliability. Cronbach's alpha coefficients ranged from 0.718 to 0.862, demonstrating acceptable internal consistency across constructs. Composite reliability (CR) values varied between 0.719 and 0.862, exceeding the recommended cutoff of 0.70 and further supporting construct reliability.

Average variance extracted (AVE) exceeded the 0.50 threshold for most constructs, including AICAF, TC, USC, and AP. Although Technology Overload (AVE = 0.463), Technological Invasion (AVE = 0.491), and Well-being (AVE = 0.486) exhibited marginally lower AVE values, these constructs were retained because

their CR values exceeded 0.70, consistent with the criteria proposed by Fornell and Larcker (1981). Overall, the results support adequate reliability and convergent validity of the measurement model.

4.3.3 Discriminant Validity

Discriminant validity was assessed using the HTMT criterion, which has been shown to be more sensitive than the Fornell–Larcker criterion in detecting discriminant validity issues.

Table 3
Heterotrait–Monotrait Ratio (HTMT)

Construct	1	2	3	4	5	6	7
1. AICAF	—						
2. TechnoOverload (TO)	0.192	—					
3. TechnoComplexity (TC)	0.258	0.331	—				
4. TechnoInvasion (TI)	0.238	0.274	0.453	—			
5. Social Upward Comparison (USC)	0.242	0.275	0.138	0.190	—		
6. Academic Pressure (AP)	0.162	0.303	0.281	0.241	0.410	—	
7. Well-being (WB)	0.270	0.153	0.103	0.175	0.090	0.167	—

Discriminant validity was further assessed using the Heterotrait–Monotrait ratio of correlations (HTMT). According to the recommended threshold, HTMT values below 0.85 (or 0.90 for conceptually related constructs) indicate adequate discriminant validity. The results showed that all HTMT values ranged from 0.090 to 0.453, well below the conservative cutoff value of 0.85. These findings suggest that all constructs in the measurement model are empirically distinct and demonstrate satisfactory discriminant validity.

4.4 Structural Model Results

4.4.2 Structural Model Fit and Path Estimates

Figure 2 presents the standardized structural model results. The overall structural model demonstrated good fit to the data ($\chi^2/df = 1.49$, CFI = .946, TLI = .940, RMSEA = .038), indicating that the hypothesized relationships were consistent with the observed covariance structure.

In terms of direct effects, AI-curated academic feeds (AICAF) significantly predicted the three technostress dimensions, including technology overload (β = .22), technological complexity (β = .30), and technological invasion (β = .24). However, none of the technostress dimensions significantly predicted well-being (β = −.07, .02, and − .12, respectively), suggesting that technology-related strain did not directly translate into diminished psychological well-being in the presence of other mechanisms.

AICAF was positively associated with upward social comparison (β = .27), which in turn significantly predicted academic pressure (β = .41). Academic pressure showed a marginal negative association with well-being (β = −.13, p = .054), indicating that higher perceived academic demands were linked to lower levels of psychological well-being.

The model explained 3.7% of the variance in well-being. Although modest, this level of explained variance is not unexpected given the distal and multifactorial nature of psychological well-being. The model explained 16.5% of the variance in academic pressure and 7.1% in upward social comparison. Overall, these results suggest that the primary explanatory pathway operates through social–evaluative mechanisms rather than direct technostress effects.

4.4.3 Direct Effects and Hypothesis Testing

Table 6
Direct Effects and Hypothesis Testing Results

Hypothesis	Path	β (standardized)	p-value	Decision
H1a	AI Curated Academic Feed (AICAF) → TechnoOverload (TO)	0.219	.002	Supported
H1b	AI Curated Academic Feed (AICAF) → TechnoComplexity (TC)	0.298	< .001	Supported
H1c	AI Curated Academic Feed (AICAF) → TechnoInvasion (TI)	0.245	< .001	Supported
H2a	Techno-overload (TO) → Well-being (WB)	−0.059	.348	Not supported
H2b	Techno-complexity (TC) → Well-being (WB)	0.019	.739	Not supported
H2c	Techno-invasion (TI) → Well-being (WB)	−0.117	.087	Not supported
H4	AI Curated Academic Feed (AICAF) → Upward Social Comparison (USC)	0.266	< .001	Supported
H5	Upward Social Comparison (USC) → Academic Pressure (AP)	0.407	< .001	Supported
H6	Academic Pressure (AP) → Well-being (WB)	−0.128	.054	Not supported

Table 6 summarizes the direct effects corresponding to the proposed hypotheses. AI-curated academic feeds significantly predicted technostress dimensions and upward social comparison, and upward social comparison significantly increased academic pressure. Although the direct effect of academic pressure on well-being did not reach conventional significance levels (p = .054), subsequent mediation analyses

focused on indirect effects estimated via bootstrapping, consistent with a mechanism-based interpretation of the proposed model.

4.4.4 Mediation and Indirect Effects

Table 7
Mediation and Serial Mediation Analysis Results

Hypothesis	Indirect Path	Indirect Effect	95% BC CI	Decision
H3a	AICAF → TechOverload → WB	≈ 0	CI includes 0 / collapsed	Not supported
H3b	AICAF → TechComplex → WB	≈ 0	CI includes 0 / collapsed	Not supported
H3c	AICAF → TechInvasion → WB	≈ 0	CI includes 0 / collapsed	Not supported
H7	USC → AP → WB	−0.050	[− 0.105, − 0.001]	Supported
H8	AICAF → USC → AP → WB	−0.045	[− 0.095, − 0.013]	Supported

To examine indirect effects, a bias-corrected bootstrapping procedure with 5,000 resamples was employed in AMOS. The results revealed a significant serial mediation effect, whereby AI-curated academic feeds increased upward social comparison, which subsequently elevated academic pressure and, in turn, reduced students' well-being. The bias-corrected 95% confidence interval for this sequential indirect effect did not include zero, indicating statistical significance.

Although the direct effect of academic pressure on well-being did not reach conventional levels of statistical significance, the bias-corrected bootstrap results indicate that its role within the indirect pathway remains substantively meaningful. Taken together, these findings are more consistent with an indirect-only associative pattern than with a robust direct association.

In contrast, indirect effects through technostress dimensions were not supported, as their bias-corrected confidence intervals included zero. Overall, the findings suggest that technology-related strain does not translate into well-being outcomes once evaluative mechanisms are accounted for, rather than reflecting measurement inadequacy.

5. Discussion

This study sought to clarify the psychological mechanisms through which AI-curated academic feeds influence university students' mental well-being. Empirically, three patterns emerged. First, AI-curated academic feeds did not directly predict well-being. Second, technostress dimensions were not significant mediators. Third, a significant serial mediation pathway was identified through upward social comparison and academic pressure.

Rather than exerting an immediate or direct impact, the findings demonstrate that the effects of AI-curated academic feeds are transmitted primarily through indirect socio-psychological pathways. In particular, upward social comparison and academic pressure emerge as central mechanisms that sequentially convey the influence of algorithmically curated academic content to students' well-being.

5.1 AI-curated academic feeds (AICAF) and Upward Social Comparison

The results indicate that AI-curated academic feeds significantly increase upward social comparison among university students. At the mechanism level, algorithmic personalization tends to prioritize the visibility of high-achievement–oriented academic content, including exemplary performance outcomes, outstanding scholarly accomplishments, and idealized learning trajectories. Repeated exposure to such content increases the salience of elevated achievement standards, making it more likely that students evaluate their own academic standing relative to superior referents.

This pattern is consistent with Social Comparison Theory (Festinger, 1954), which posits that individuals assess their abilities and self-worth by comparing themselves with others, particularly in environments rich in evaluative information. In AI-curated academic feeds, this process is amplified by algorithmic selection and repetition, which continuously reinforce specific performance norms. The findings extend prior research on algorithmic curation and social comparison in digital environments to academic contexts, where curated content is closely tied to achievement norms rather than entertainment or social visibility alone.

5.2 Upward Social Comparison and Academic Pressure

Upward social comparison emerged as a significant antecedent of academic pressure. When students repeatedly compare themselves to peers who appear to perform better, they are more likely to internalize elevated achievement standards as benchmarks for self-evaluation. This process transforms social comparison into a form of social benchmarking, in which students perceive the learning environment as increasingly competitive and outcome-oriented.

From an educational psychology perspective, such benchmarking intensifies self-imposed expectations and heightens sensitivity to perceived academic demands. As students strive to align their performance with superior standards observed in their environment, academic pressure becomes a proximal psychological response. This finding aligns with prior research showing that comparison-based evaluative processes play a critical role in shaping achievement-related pressure in higher education settings.

5.3 Academic Pressure and Well-being

Academic pressure showed a marginal and indirect association with students' well-being, highlighting its role as a proximal psychological factor shaping everyday learning experiences. Persistent exposure to high performance expectations, perceived competition, and evaluative demands can gradually erode

students' psychological resources. Over time, these pressures may contribute to emotional strain, reduced motivation, and lower overall life satisfaction, consistent with research on academic stress and burnout.

Importantly, the absence of a significant direct effect suggests that academic pressure does not immediately undermine well-being, but rather exerts its influence through cumulative psychological strain. This pattern underscores the importance of considering well-being as an outcome shaped by sustained exposure to achievement-related demands rather than isolated stressors.

5.4 Serial Mediation through Upward Social Comparison and Academic Pressure

A key contribution of this study lies in identifying a sequential mediation mechanism linking AI-curated academic feeds to students' well-being. The findings indicate that AI-curated academic feeds first shape students' evaluative perceptions by increasing exposure to performance-oriented content, thereby intensifying upward social comparison. This comparison process is subsequently internalized as academic pressure, which, over time, undermines well-being.

This serial mediation pattern highlights that the effects of AI-curated academic feeds unfold gradually through interconnected socio-psychological processes rather than through direct technological strain. Upward social comparison functions as an initial cognitive-evaluative response, while academic pressure represents a more proximal psychological consequence that directly precedes changes in well-being. Together, these mechanisms form a coherent explanatory chain that clarifies how algorithmically curated academic environments shape students' psychological experiences.

Notably, this mechanism differs from traditional technostress models that emphasize cognitive overload or resource depletion. Instead, the present findings suggest that AI-curated academic feeds primarily operate through evaluative processes rather than technological strain, thereby shifting the analytical focus from resource-based stress to performance-based self-evaluation.

The relatively modest R^2 for well-being should be interpreted in light of the distal and multifactorial nature of psychological well-being. Well-being is shaped by dispositional traits, social relationships, economic factors, and broader life circumstances that extend beyond digital academic exposure (Funder & Ozer, 2019).The present model was not designed to maximize predictive power but to test a theoretically specified evaluative mechanism linking AI-curated academic feeds to well-being via upward social comparison and academic pressure.

5.5 Why the Effects Operate Indirectly Rather Than Directly

The findings indicate that the relationship between AI-curated academic feeds and student well-being operates primarily through indirect, mediated pathways rather than immediate exposure effects. In the proposed model, well-being was conceptualized as a distal outcome shaped by intervening socio-psychological processes, rather than as a direct consequence of AI-curated content.

Rather than producing immediate negative consequences, AI-curated academic feeds appear to reshape the evaluative context through which students interpret their academic experiences. Repeated exposure to elevated performance norms and peer comparison cues may gradually intensify upward social comparison and perceived academic pressure, which accumulate over time and ultimately influence psychological well-being.

This mediated pattern is consistent with process-oriented perspectives in psychology, which emphasize that distal outcomes such as well-being are typically influenced by layered and cumulative mechanisms rather than direct exposure effects. The findings therefore caution against simplistic interpretations of technology–well-being relationships and underscore the importance of examining intermediary socio-psychological processes in AI-driven learning environments.

5.6 The Limited Role of Technostress

Contrary to theoretical expectations, technostress did not emerge as a statistically supported mediating mechanism between AI-curated academic feeds (AICAF) and student well-being within the specified model and the studied context. Although AICAF was positively associated with all technostress dimensions, these technology-related strains did not translate into significant indirect effects on well-being once social–evaluative mechanisms were taken into account.

In contrast, socio-psychological pressures arising from social comparison and achievement expectations appear to constitute more salient and psychologically consequential pathways through which AI-curated academic feeds are associated with student well-being. These findings highlight the importance of distinguishing between instrumental technology-related strain and evaluative pressures when examining the psychological consequences of AI-driven learning environments.

An alternative explanation is that technostress may manifest more strongly in proximal outcomes, such as momentary fatigue, concentration difficulties, or task-specific disengagement, rather than in global well-being as measured in the present study. The well-being construct employed here reflects a broad and relatively distal psychological state, capturing overall mental health and life satisfaction rather than immediate or situation-specific strain. As a result, technology-related stress responses may not be sufficiently proximal or intense to exert detectable effects on such an outcome within a cross-sectional design.

Future research may therefore benefit from examining technostress effects on more domain-specific or short-term outcomes, or from adopting experience-sampling or longitudinal designs that are better suited to capturing fluctuations in technology-related strain over time. Such approaches may provide a more sensitive assessment of how technostress operates across different temporal and psychological levels.

Although technostress was theoretically expected to be negatively associated with student well-being (H2), this relationship was not empirically supported in the present study, indicating that technology-

related strain alone may not translate into diminished well-being once evaluative and achievement-related mechanisms are accounted for.

These findings suggest that, within algorithmically curated academic environments, evaluative mechanisms may override purely technological strain in shaping psychological outcomes.

5.7 Theoretical Contributions

This study contributes to Social Comparison Theory by extending its application to AI-curated academic contexts. The findings demonstrate that algorithmic selection and repetition of academic content actively shape evaluative standards and comparison processes, positioning algorithms as influential agents in the construction of academic norms. In addition, the study advances research on student well-being by elucidating a sequential mediation mechanism through which AI-curated academic feeds exert indirect effects via upward social comparison and academic pressure.

By adopting a mechanism-focused perspective, the study moves beyond establishing direct associations between technology use and well-being and offers a theoretically grounded explanation of how AI-driven systems influence students' psychological experiences over time.

The present findings reposition algorithmic curation not merely as a source of technological strain, but as a norm-amplifying mechanism that reshapes evaluative environments within higher education.

5.8 Practical Implications

For universities and instructors, the findings underscore the importance of managing the socio-psychological consequences of AI-curated academic content. Pedagogical strategies may place greater emphasis on individual learning progress, diverse indicators of success, and mastery-oriented goals in order to reduce excessive achievement-oriented comparisons. Student support initiatives may also benefit from addressing the accumulation of academic pressure, particularly during high-stakes assessment periods.

For platform designers and AI system developers, the findings suggest that, in educational contexts, excessive amplification of exceptional achievement content may warrant attention when designing AI-curated academic feeds, particularly where student well-being is a concern. However, further longitudinal and experimental research is required before translating these insights into concrete system-level design guidelines. Such considerations may help mitigate upward social comparison and support digital learning environments that are more attuned to students' long-term psychological well-being.

6 Limitations and Future Research

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design restricts causal inference and limits insight into the temporal dynamics of the proposed mechanisms. Although the model was theoretically grounded, future research using longitudinal or experimental designs would be valuable in examining how prolonged

exposure to AI-curated academic feeds shapes upward social comparison, academic pressure, and well-being over time.

Second, the study relied on self-reported data, which may be subject to common method bias and subjective interpretation. While established procedural and statistical controls were applied, future studies could strengthen measurement validity by incorporating multi-source data, such as platform usage logs, learning analytics, or behavioral indicators of academic engagement and stress.

Third, the explained variance in well-being was modest, reflecting the inherently multifaceted and distal nature of psychological well-being. The present study intentionally adopted a mechanism-focused approach, concentrating on specific socio-psychological pathways rather than maximizing predictive power. Future research may extend the model by integrating additional mediators or moderators, such as academic self-efficacy, learning motivation, resilience, or perceived academic competence, to capture a broader range of influences on well-being.

Finally, the sample was drawn from a specific higher education context, which may constrain the generalizability of the findings. Replication across diverse cultural, institutional, and educational settings would help evaluate the robustness and boundary conditions of the proposed mechanism. Future research may also integrate additional dispositional and contextual predictors to expand explanatory scope and further delineate the conditions under which AI-curated academic environments influence student well-being.

Declarations

Participation in this study was voluntary and involved minimal risk. Participants were informed about the purpose of the study prior to data collection, could skip any question they did not wish to answer, and were free to withdraw from the study at any time without penalty. No personally identifiable information was collected, and all responses were anonymous and treated confidentially.

Ethical Approval

This study was reviewed and approved by the Board of Directors of FPT Can Tho University, Vietnam, with Approval No. SU25.06.01, dated 19th June 2025. The study complied with institutional research ethics guidelines. Written informed consent was obtained from all participants prior to data collection. Confidentiality and anonymity were maintained throughout the research process.

Author Contribution

"Phu.N.H.H. and Luan.T.N. wrote the main manuscript text and all authors prepared all figures and Tables . All authors reviewed the manuscript

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Figures

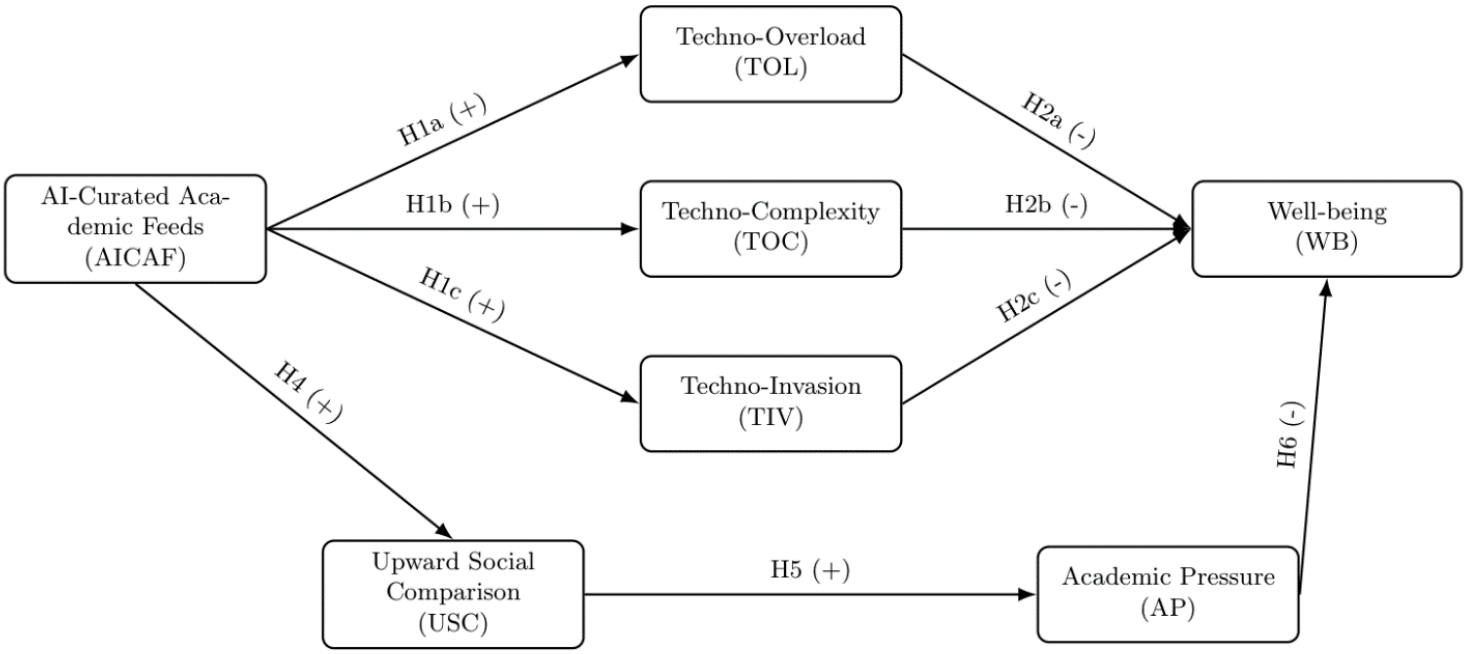


Figure 1: Structural model with direct hypotheses (H1a–H2c, H4–H6).

- **H3a** proposes that TOL mediates the relationship between AICAF and WB, resulting in a negative indirect effect (AICAF → TOL → WB).
- **H3b** proposes that TOC mediates the relationship between AICAF and WB, resulting in a negative indirect effect (AICAF → TOC → WB).
- **H3c** proposes that TIV mediates the relationship between AICAF and WB, resulting in a negative indirect effect (AICAF → TIV → WB).
- **H7** proposes that AP mediates the relationship between USC and WB, resulting in a negative indirect effect (USC → AP → WB).
- **H8** proposes that USC and AP sequentially mediate the relationship between AICAF and well-being, resulting in a negative indirect effect (AICAF → USC → AP → WB).

Figure 1

Structural model illustrating the direct structural paths (H1a–H2c, H4–H6). Mediation hypotheses (H3a–H3c, H7–H8) are tested via indirect effects using bootstrapping procedures and are therefore not depicted in the figure.

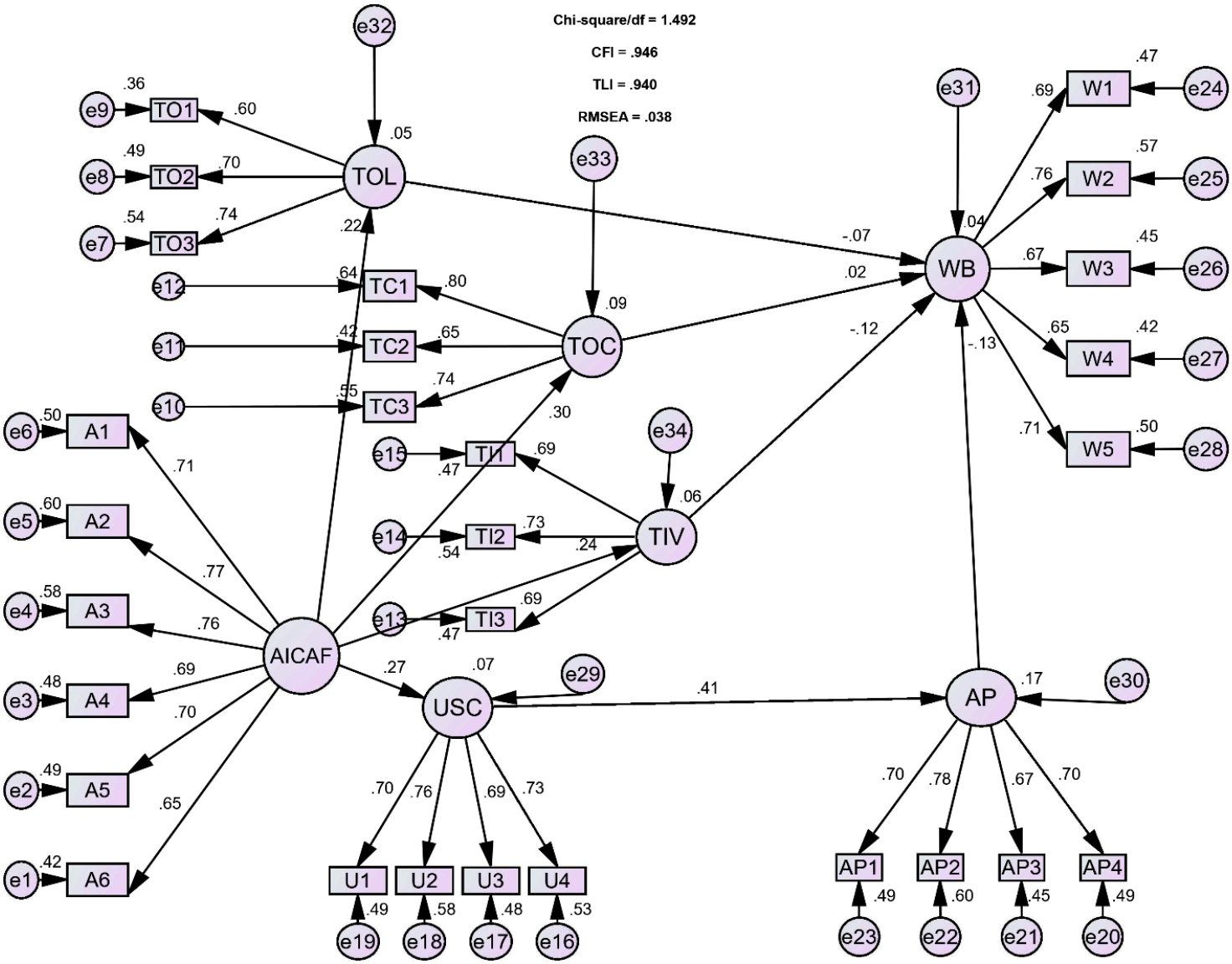


Figure 2

Proposed structural model and standardized path coefficients.