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ARTICLE

Developing Sustainable Competitive Intelligence Capabilities Through Virtual Reality and Experiential Learning: A Technology Acceptance-Based Framework

Desenvolvendo Capacidades de Inteligência Competitiva Sustentável por meio de Realidade Virtual e Aprendizagem Experiencial: Um Modelo Baseado na Aceitação Tecnológica

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ABSTRACT | Purpose: To position Competitive Intelligence (CI) as the epistemological axis of a proposed VR-experiential learning framework for Sustainable Competitive Intelligence (SCI), and to ground the framework's acceptance-related design parameters in an empirical needs assessment of undergraduate students' technology acceptance. **Methodology/ approach:** Secondary quantitative analysis of a validated Technology Acceptance Model (TAM) survey of 150 Chinese undergraduate students, using descriptive statistics, composite reliability and discriminant validity analysis, correlation, OLS regression with full diagnostic testing, and a sensitivity analysis of the item-coding decision. **Originality/ Relevance:** Competitive Intelligence education research offers limited empirical guidance on immersive instructional design; this study develops a conceptual matrix linking a VR-experiential learning framework to every stage of the CI cycle, explicitly distinguishing this conceptual contribution from its bounded empirical evidence on general VR acceptance. **Key findings:** Attitude, perceived usefulness, and innovativeness significantly predicted behavioral intention to adopt VR ($R^2 = .32$); perceived ease of use did not. Prior VR experience raised perceived ease of use but lowered behavioral intention. All constructs met composite reliability, average variance extracted, and discriminant validity thresholds. **Theoretical/ methodological contributions:** The study integrates the CI cycle, dynamic capabilities, and Kolb's experiential learning cycle into a stage-by-stage conceptual matrix, and demonstrates, using the original instrument's item wording as documentary evidence, why raw item coding rather than codebook-reversed coding was retained.

Keywords | Competitive intelligence. Competitive intelligence cycle. Virtual reality. Experiential learning. Technology acceptance model. Dynamic capabilities. Sustainable competitive advantage. Undergraduate students.

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RESUMO | Objetivo: Posicionar a Inteligência Competitiva (IC) como o eixo epistemológico de um modelo proposto de aprendizagem experiencial com realidade virtual (RV) para a Inteligência Competitiva Sustentável (ICS), fundamentando os parâmetros de aceitação do modelo em uma avaliação empírica das necessidades dos estudantes de graduação. **Metodologia/abordagem:** Análise quantitativa secundária de um levantamento validado baseado no Modelo de Aceitação de Tecnologia (TAM), aplicado a 150 estudantes de graduação chineses, utilizando estatística descritiva, confiabilidade composta e validade discriminante, correlação, regressão OLS com diagnóstico completo, e uma análise de sensibilidade da codificação dos itens. **Originalidade/Relevância:** A pesquisa em educação de Inteligência Competitiva oferece orientação empírica limitada sobre o design instrucional imersivo; este estudo desenvolve uma matriz conceitual que conecta um modelo de RV e aprendizagem experiencial a cada etapa do ciclo de IC, distinguindo explicitamente essa contribuição conceitual de sua evidência empírica delimitada sobre a aceitação geral de RV. **Principais conclusões:** Atitude, utilidade percebida e inovatividade previram significativamente a intenção comportamental de adotar a RV (R^2 = 0,32); a facilidade de uso percebida não foi significativa. A experiência prévia com RV elevou a facilidade de uso percebida, mas reduziu a intenção comportamental. Todos os construtos atenderam aos critérios de confiabilidade composta, variância média extraída e validade discriminante. **Contribuições teóricas/metodológicas:** O estudo integra o ciclo de IC, as capacidades dinâmicas e o ciclo de aprendizagem experiencial de Kolb em uma matriz conceitual detalhada por etapa, e demonstra, com base na redação original dos itens do instrumento como evidência documental, por que a codificação bruta, e não a codificação invertida do codebook, foi mantida.

Palavras-chave | Inteligência competitive. Ciclo de inteligência competitive. Realidade virtual. Aprendizagem experiencial. Modelo de aceitação de tecnologia. Capacidades dinâmicas. Vantagem competitiva sustentável. Estudantes de graduação.

1 INTRODUCTION

Competitive Intelligence (CI) can be defined as a systematic process of planning, collecting, environmental scanning, analyzing, communicating, and feeding back information about competition and the external business environment to inform strategic decision making, with a governance and feedback loop to redirect and inform future planning (Markovich, Raban, & Efrat, 2022; Maungwa & Laughton, 2023). What makes CI "cyclical" and different from ad hoc market research is the ability of the firm to maintain the cycle in a rapidly changing environment—it is not determined by the quality of any one report. As stated in the above, when framed in this way, CI cannot be separated from the dynamic-capabilities view of the firm, which emphasizes the ability of an organization to sense opportunities and threats in the external environment, seize them, and reconfigure its resources to capture the opportunities and neutralize threats (Markovich et al., 2022; Ellström, Holtström, Berg, & Josefsson, 2022). For the purposes of this paper, Sustainable Competitive Intelligence (SCI) is defined as this capability-based reading of CI, an intelligence function whose value lies in its capacity to become a constant renewal process, based upon organizational learning and the knowledge-based view of the position of the firm in a competitive environment (Baker, Mukherjee, & Gattermann Perin, 2022; Zhang, Chu, Ren, & Xing, 2023).

This capability-based framing has a direct pedagogical implication. Undergraduate CI should develop the specific skills that enable the organization to sense, analyse, and react to its environment, not just share a set of pre-set scenarios like Porter's five forces or SWOT analysis through lectures and case studies (Maungwa & Laughton, 2023). Traditional CI teaching does not provide much opportunity for students to perform the iterative cyclical process of professional CI. This deficit fuels the interest in pedagogies that are experiential and technology-supported and that can model the CI cycle, from scanning to analysis to dissemination, in the classroom.

Virtual reality (VR) is one candidate technology for this purpose, and immersive simulation is increasingly used to rehearse complex, multi-stage professional tasks under realistic but low-stakes conditions (Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020). However, immersion alone does not develop intelligence competencies: a VR environment must be deliberately structured so that learners cycle through the stages of environmental scanning, analysis, and reflective judgment that the CI cycle requires, rather than simply experiencing a novel medium (Makransky & Petersen, 2021). Kolb's experiential learning cycle, comprising concrete experience, reflective observation, abstract conceptualization, and active experimentation, offers a structuring logic for converting a VR-based CI simulation into durable analytical competency (Kolb, 1984; Kolb & Kolb, 2022).

Before such a framework can be responsibly proposed, however, its design parameters must be grounded in evidence of whether the target learner population is prepared to accept the immersive technology on which it depends. It is important to state this precisely and at the outset: the present study's empirical component measures general VR technology acceptance among Chinese undergraduate students, using constructs drawn from the Technology Acceptance Model (TAM), specifically perceived usefulness, perceived ease of use, innovativeness, attitude toward using, and behavioral intention (Davis, 1989; Ji, Indieka, Sun, Chong, & Quan, 2026). These constructs are not measures of Competitive Intelligence capability, CI competencies, execution of the intelligence cycle, environmental scanning, or intelligence governance. The empirical contribution of this paper is therefore deliberately bounded: it establishes the acceptance-related conditions, such as which beliefs most strongly predict behavioral intention, that any VR-based CI curriculum would need to satisfy for learners to engage with it at all. The conceptual contribution of this paper, developed separately in Section 2 and formalized in Table 1, is a matrix that maps the stages of the CI cycle onto specific VR-experiential learning mechanisms, the CI competencies each mechanism is intended to develop, and the indicators by which that development could, in future research, be assessed. The paper treats these two contributions as distinct throughout, and it does not present the empirical TAM findings as validation of the conceptual CI framework.

Accordingly, this study pursues two objectives. First, it develops Competitive Intelligence, structured around the full CI cycle, as the epistemological axis of a VR-experiential learning framework, explicitly connecting dynamic capabilities, the knowledge-based view, and organizational learning to the mechanisms by which VR and experiential learning could plausibly develop CI competencies. Second, it examines the technology acceptance patterns of Chinese undergraduate students toward VR-based learning, in order to identify the acceptance-related design parameters that this framework must accommodate before empirical testing of its CI-specific effectiveness becomes feasible. Section 2 develops the theoretical framework and the conceptual matrix. Section 3 describes the data source, instrument, and analytical procedures, including a sensitivity analysis of the coding decisions applied to the data. Section 4 presents the empirical results, interpreted throughout in relation to their bearing on the CI cycle rather than as evidence about CI itself. Section 5 states plainly what the study does and does not demonstrate, and outlines the empirical validation the proposed framework still requires.

2 THEORETICAL FRAMEWORK

Section titles are written in capital letters, and at least one paragraph separates a title from any subsequent subtitle. This section positions Competitive Intelligence, structured around its full cycle, as the epistemological axis of the study, before introducing virtual reality, experiential learning theory, and the Technology Acceptance Model as, respectively, the candidate instructional medium, the pedagogical mechanism, and the empirical lens through which undergraduate readiness for that medium is assessed. Section 2.5 integrates these elements into a conceptual matrix that links each stage of the proposed VR-experiential learning framework to a specific CI competency and expected indicator.

2.1 The competitive intelligence cycle and sustainable competitive advantage

Competitive Intelligence should be viewed as a process, not an analysis. Across the process-oriented accounts of CI, the cycle includes consistently: planning and direction, collection, environmental scanning, analysis, dissemination, utilization in decision making, and a governance and feedback stage which re-directs the next round of planning (Markovich, Raban, & Efrat, 2022; Maungwa & Laughton, 2023). Planning and direction determines which intelligence questions are important to the organisation; collection and environmental scanning acquires signals from the competitive environment, such as customers, competitors, regulators and technological trends; analysis converts these signals into patterns that are interpretable; dissemination conveys the results of the analysis in a meaningful form to decision makers; utilization involves the incorporation of intelligence into a decision; governance and feedback assess the value add achieved by the cycle in the context of the decision. It is not any single stage, but rather this closed loop, self-correcting structure, that translates CI to the dynamic-capabilities view of the firm, which focuses on sensing opportunities and threats, taking them up, and reconfiguring resources when necessary (Markovich et al., 2022; Ellström, Holtström, Berg, & Josefsson, 2022). Environmental scanning and analysis are similar to sensing, while dissemination and utilization are similar to seizing, and governance and feedback are similar to reconfiguring, as it is in this stage that the organization readjusts how it is scanning, analyzing, and responding to its environment based on the results of the previous cycle.

This is because the sustainability qualifier is a capability reading of CI. In contrast to the usage of the word sustainable in the strategy literature, security obtained by one good product of intelligence is not sustainable but must be continually renewed so that the capability can be reproduced effectively as the environment changes (Baker, Mukherjee, & Gattermann Perin, 2022; Amiri, Shirkavand, Chalak, & Rezaeei, 2017). Empirical studies of SMEs have confirmed that competitive intelligence activities are important to improve the dynamic capabilities of the firm and its subsequent adaptation to the dynamic business environment, which shows that the real value of competitive intelligence is not a one-time report, but rather in the repetitive organizational routines used to generate and apply the intelligence (Wu, Yan, & Umair, 2023). The way these renewals occur is through organizational learning: Firms that institutionalize both exploratory and exploitative learning around their intelligence routines are more likely to sustain competitive advantage over firms that do not institutionalize each intelligence cycle as an isolated event (Zhang, Chu, Ren, & Xing, 2023; Azeem, Ahmed, Haider, et al., 2021). The knowledge-based view of the firm adds to this account by characterizing the intelligence the firm generates in the process of the CI cycle as its most strategically important resource, just because it is hard for competitors to imitate when it is embedded in the firm's routines, as opposed to being stored and recorded as information (Baker et al., 2022). Also from the environmental scanning research is the finding that systematic scanning firms outperform firms that do not, and that in the face of volatile conditions scanning has become a vehicle for firms' competitive adjustment (Harris & Brooker, 2025).

The advantage of the CI cycle can be better captured by the notion of information asymmetry, which occurs when one party of a decision has systematically better information than the other (Akerlof, 1970). A firm that does the CI cycle well reduces the distance between what they know about their competitive environment and what their competitors know and it is that distance, not any single competitor fact, that gives them the strategic choices they would make better if they knew more (Fadhlurrahman, Riyanta, & Ras, 2024). The meaning of the intelligence generated in the cycle lies in its strategic nature, in the sense that it is synthesized, decision-relevant, and addressed to the positioning and allocation of resources for the long-term. This is what connects the cycle and the governance stage to the dynamic-capabilities and knowledge-based accounts of competitive advantage discussed above, that is, when the output of the intelligence cycle has a strategic nature (Fadhlurrahman et al., 2024; Markovich et al., 2022).

One common theme in this literature is that the benefit of CI is achieved through governance of the whole cycle and not on the sophistication of any one part. An intelligence collection without governance leads to information overload, analysis without dissemination pathway to an intelligence failure, and utilization without feedback to the organization to a failure of the organization to learn whether or not its intelligence process is actually improving decisions (Markovich et al., 2022). Educational intervention should be judged by whether it reflects and analyzes the entire cycle of governance, not just an isolated analytical skill, which is directly relevant to CI education, as is done throughout the rest of this paper.

2.2 Virtual reality as a candidate medium for simulating the ci cycle

Virtual reality (VR) is the name given to three-dimensional environments that are created by computers and onto which users interact in real time using a head-mounted display or other immersive interface (Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020). This extrapoladation of VR in specific contexts of coursework is occurring in the midst of the digital transformation that has been taking place in higher education institutions, where specific technologies have been embraced at different rates across administrative, teaching, and research activities, with classroom-use technologies (like VR) lagging behind administrative digitalisation (Benavides, Tamayo Arias, Arango Serna, Branch Bedoya, & Burgos, 2020). In higher education, VR has been used in a variety of subjects from health sciences to engineering, in which a series of complex steps in a professional task are simulated; the same reasoning applies to CI: in theory, the simulated competitive environment could require students to scan the environment for signals, decide what to collect, analyze what they find, and disseminate a recommendation, which would follow the CI cycle, rather than just a static case exercise. By conducting a systematic review of immersive VR apps for higher education, Radianti et al. (2020) found design features like guided task structure, feedback mechanisms and staged progression that were consistently associated with educationally valuable VR use cases and not just novelty-based ones. The evidence from a meta-analysis supports the claim that VR-based instruction is related to measurable learning gains when compared to traditional instruction in general, with somewhat higher effect sizes in certain content domains, for younger learners, and for the development of emotional engagement, in addition to cognitive gains (Villena-Taranilla, Tirado-Olivares, Cózar-Gutiérrez, & González-Calero, 2022; Yu & Xu, 2022; Wang & Pan, 2025).

Another theme that has been repeated in this literature, and one that is especially relevant to CI, is that immersion does not promise learning, and that the goal of CI is not sensory immersion, but disciplined analytical judgement. The Cognitive Affective Model of Immersive Learning theorizes that the presence and emotional engagement surrounding immersive learning, which influences subsequent cognitive processing, have the potential to impact the learning outcome indirectly (Makransky & Petersen, 2021). Whether it has a high or low visual fidelity, a VR simulation that only introduces the learner into a convincing market situation, but doesn't ask the learner to develop a scanning plan, process the information collected, or draw a conclusion, would not represent a CI-competency intervention. VR-based CI simulations should therefore be conceived as a series of tasks with a clear and predictable structure that are clearly related to the phases of the CI cycle, and not as free exploration settings.

A second, closely related literature investigates the conditions that make learners want to use virtual reality technology in the first place, which is a logical question prior to whether a CI-specific VR intervention can be used as intended. The present study uses this literature to provide the empirical lens that allows for a study of undergraduate readiness for VR-based instruction, ahead of any specific implementation of CI in the context.

2.3 Experiential learning theory as the mechanism linking vr to ci competency

Experiential learning theory conceptualises learning as a continuous cycle in which concrete experience is transformed into knowledge through reflective observation, abstract conceptualization, and active experimentation, with each stage feeding back into subsequent experience (Kolb, 1984). This structure is what allows VR to be positioned as more than an engagement tool for CI education: a VR-based competitive-environment simulation supplies only the concrete experience stage, corresponding to the collection and environmental scanning stages of the CI cycle. Without deliberately designed reflective observation, in which learners examine what signals they scanned for and why, abstract conceptualization, in which learners generalize principles about analysis and dissemination, and active experimentation, in which learners apply updated strategies in a new scenario, the CI-relevant value of the simulation is unlikely to be realized (Kolb & Kolb, 2022).

This is not a hypothetical concern. A recent intervention study in nursing education that deliberately implemented all four stages of the Kolb cycle, pairing case-based simulation with structured reflective journaling, mind-mapping for conceptualization, and peer-led simulation for active experimentation, produced significantly higher self-directed learning and critical thinking scores than a comparison cohort exposed to conventional instruction (Cheng, Wu, Huang, Wu, & Guan, 2025). The mechanism is directly transferable to CI education: reflective observation is the pedagogical analogue of the CI cycle's governance and feedback stage, since both require the learner, or the organization, to evaluate whether the preceding scanning and analysis actually produced usable insight before proceeding. The proposed framework in Section 2.5 treats VR not as a standalone instructional tool but as the experiential anchor of a complete Kolb cycle explicitly mapped onto the stages of CI.

2.4 The technology acceptance model as a needs-assessment lens, not a ci measure

The Technology Acceptance Model, originally developed by Davis (1989), proposes that an individual's behavioral intention to use a technology is shaped by two core beliefs, perceived usefulness and perceived ease of use, which jointly influence attitude toward using the technology and, subsequently, behavioral intention. Later extensions broadened the model to account for voluntary-use and organizational contexts (Venkatesh & Bala, 2008), and the model has since been extended repeatedly to accommodate additional constructs relevant to specific technologies and populations. In immersive and virtual reality contexts, extended TAM specifications commonly incorporate individual innovativeness, defined as an individual's disposition to adopt new technologies ahead of peers, both as an antecedent of perceived usefulness and ease of use and as a direct predictor of behavioral intention (Sagnier, Loup-Escande, Lourdeaux, Thouvenin, & Valléry, 2020; Jang, Ko, Shin, & Han, 2021). Applied specifically to VR-based instruction, extended TAM models confirm that immersion-related beliefs strengthen the conventional usefulness and ease-of-use pathways among both adult and younger learners (Fussell & Truong, 2022, 2023; Villena-Taranilla, Cózar-Gutiérrez, González-Calero, & Diago, 2023). Broader systematic reviews of educational technology adoption (Granić, 2022) and of metaverse-specific adoption in particular (Al-kfairy, Ahmed, & Khalil, 2024; Almeman, EL Ayeb, Berrima, Issaoui, & Morsy, 2025) confirm that TAM remains the dominant explanatory framework in this literature, increasingly supplemented by constructs such as personal innovativeness (Al-Adwan & Al-Debei, 2024) and immersion-specific acceptance mechanisms (Nilashi & Abumalloh, 2025).

Cross-cultural applications of TAM to VR acceptance in education, including a recent comparative study of Chinese and African university students and teachers, confirm that the core TAM pathways hold across cultural contexts while also showing that absolute acceptance levels, and the relative importance of specific constructs, vary meaningfully by region and by user role, with students generally showing higher acceptance than teachers (Ji et al., 2026). This role-based pattern recurs elsewhere: teachers often report more circumspect attitudes toward immersive technologies than students, reflecting concerns about implementation workload and curricular fit rather than generalized technology aversion (Khukalenko, Kaplan-Rakowski, An, & Iushina, 2022; Meccawy, 2023), while cross-national comparisons further confirm that infrastructural capacity and cultural context jointly shape the practical adoption of VR for skills-based learning (Monteiro, Ma, Li, Pan, & Liang, 2024).

It is necessary to state without qualification what TAM constructs do and do not measure in the present study. Perceived usefulness, perceived ease of use, innovativeness, attitude toward using, and behavioral intention are beliefs about a technology's general educational usability. They are not measures of environmental scanning capability, analytical rigor, dissemination skill, or intelligence governance, and they do not indicate whether a learner has developed, or could develop, any CI-specific competency. Within instructional design, TAM instead functions as a needs-assessment instrument: by identifying which beliefs most strongly predict behavioral intention within a specific learner population, instructional designers can target the barriers most likely to impede adoption before a CI-specific intervention is deployed, rather than discovering these barriers only after implementation (Choi & Park, 2024). This is the sole function TAM serves in this paper, and Section 2.5 and Section 4 maintain this distinction explicitly rather than allowing TAM results to be read as evidence about CI competency development.

2.5 The proposed framework: a conceptual matrix linking vr-experiential learning to the ci cycle

Building on sections 2.1 through 2.4, this study proposes a VR-experiential learning framework for Sustainable Competitive Intelligence, illustrated in Figure 1 and specified stage-by-stage in Table 1. The framework's premise is that a VR-based CI simulation can be structured so that each stage of the CI cycle corresponds to a specific point in the Kolb experiential learning cycle, with the technology acceptance pathway determining whether learners engage with the simulation deeply enough for that structure to matter.

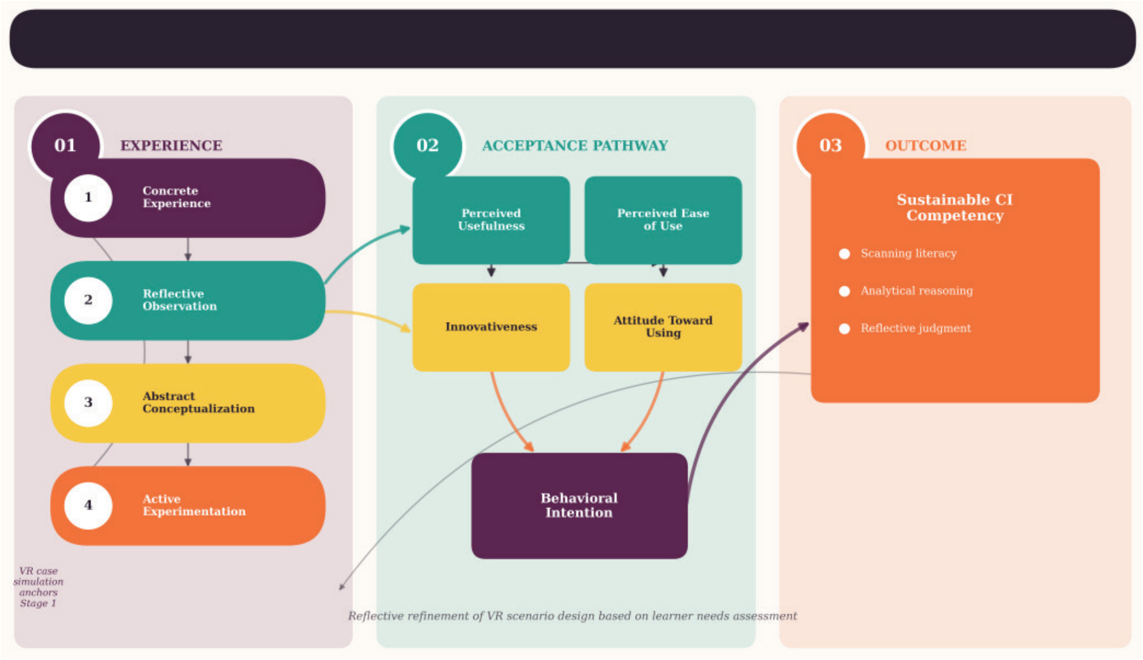

Figure 1. Proposed VR-Experiential Learning Framework for Sustainable Competitive Intelligence Education

Source: Elaborated by the authors.

Table 1 makes this mapping explicit rather than leaving it implicit in narrative description, directly addressing the concern that a VR-experiential learning framework could be proposed without demonstrating how, mechanistically, it develops CI-specific competencies rather than general technology familiarity. For each stage of the CI cycle, the table specifies the VR-experiential learning mechanism intended to engage it, the CI competency the mechanism targets, and an indicator by which future research could assess whether that competency developed.

Table 1. Conceptual Matrix Linking the VR-Experiential Learning Framework to the Competitive Intelligence Cycle

CI Cycle Stage	VR-Experiential Learning Mechanism	CI Competency Targeted	Expected Indicator (Future Research)
Planning & Direction	Pre-simulation briefing defining the intelligence question the VR task must answer	Ability to scope an intelligence requirement	Rubric-scored specificity of the question formulated
Collection	VR scenario requiring active search for embedded competitive signals (Concrete Experience)	Systematic information-gathering behavior	Number and relevance of signals identified
Environmental Scanning	Structured scanning checklist embedded in the VR task, followed by Reflective Observation on signals scanned versus missed	Environmental scanning literacy	Scanning completeness score against an expert benchmark
Analysis	Abstract Conceptualization exercise converting raw signals into strategic patterns	Analytical and interpretive reasoning	Rubric-scored accuracy and coherence of the analysis
Dissemination	Structured deliverable (brief or memo) communicating findings to a simulated decision-maker	Dissemination judgment	Clarity and actionability of the communicated intelligence
Utilization	Active Experimentation: applying the disseminated intelligence to a follow-on decision task	Decision-support application skill	Decision quality and consistency with the intelligence produced
Governance & Feedback	Guided reflection comparing outcome to the initial plan, informing redesign of the next VR scenario	Reflective governance / continuous-improvement orientation	Self- and instructor-assessed reflection quality
(Precondition) Technology Acceptance Pathway	Perceived usefulness, ease of use, innovativeness, and attitude shape willingness to engage with the VR medium	Not a CI competency — a precondition for Concrete Experience	Behavioral Intention (measured empirically in Section 4)

Source: Elaborated by the authors, drawing on Markovich, Raban, and Efrat (2022) and Maungwa and Laughton (2023).

Two features of Table 1 are central to how this paper should be read. First, the "Expected Indicator" column intentionally specifies outcomes that the present study's TAM-based dataset cannot measure, such as analytical accuracy or dissemination quality; these indicators define the empirical agenda for future implementation and evaluation of the framework, not a claim about what has already been demonstrated. Second, the technology acceptance pathway, comprising perceived usefulness, perceived ease of use, innovativeness, and attitude toward using, is positioned in the matrix as a precondition for the Concrete Experience stage rather than as a stage of the CI cycle itself: a learner who does not accept the VR medium is unlikely to engage with the scanning, analysis, or dissemination tasks embedded within it, regardless of how well those tasks are designed. This is the sense in which the empirical study reported in Sections 3 and 4, measuring TAM constructs among Chinese undergraduate students, is positioned as informing, but not validating, the framework in Table 1: it establishes whether the target learner population accepts the medium through which the

CI cycle would need to be delivered, while the CI-specific competency development mapped in Table 1 remains a proposed mechanism awaiting direct empirical test.

The framework is cyclical rather than linear, consistent with the CI cycle it is designed to simulate: insights from the reflective and governance stage are intended to inform the iterative redesign of subsequent VR scenarios, and acceptance barriers identified through needs assessment, of the kind reported in Section 4, are intended to feed back into how the VR environment itself is designed. The framework's ultimate educational outcome is not proficiency with VR technology as such, but Sustainable Competitive Intelligence competency: the combination of environmental scanning literacy, disciplined analysis, dissemination judgment, and reflective governance that supports durable, adaptive CI practice after students enter professional roles.

3 METHOD

This study adopts a quantitative, secondary-data needs-assessment design to evaluate undergraduate students' technology acceptance patterns toward VR-based learning. Consistent with Section 2.5, this design informs the acceptance-related design parameters of the framework in Table 1; it is not a test of the framework's CI-specific effectiveness. The following subsections present the research design, data source, instrument, data preparation, and analytical procedures, including a sensitivity analysis of the coding decision applied to four items.

3.1 Research design

Following needs-assessment research in instructional design, in which learner readiness data are collected and analyzed prior to, and independently of, the design of a specific instructional intervention (Choi & Park, 2024), this study conducted a cross-sectional, correlational analysis of an existing, validated TAM survey dataset. No new data collection was undertaken; instead, the study performs an independent secondary analysis of anonymized, publicly deposited survey data. This choice requires explicit justification, since secondary data collected for one purpose carries limitations when applied to a related but distinct research question. The justification offered here is twofold. First, no publicly available dataset currently measures VR acceptance specifically for CI instruction, since no such intervention has yet been implemented at the scale needed for survey research; using the closest available population, undergraduate students evaluating VR for general educational use, is consistent with standard practice in needs-assessment research, which recommends using the most relevant available learner-readiness data when purpose-built data does not yet exist (Choi & Park, 2024). Second, the alternative, delaying any empirical needs assessment until a CI-specific VR tool exists, would leave framework design entirely unconstrained by evidence of learner readiness, a worse epistemic position than the bounded, clearly labelled use of adjacent data adopted here. This justification does not extend to claims about CI-specific effectiveness, which the empirical design cannot support and which this paper does not make.

3.2 Data source, instrument origin, and participants

The data were drawn from a publicly available, de-identified dataset examining willingness to use, acceptance of, and user experience with VR devices in education among students and teachers in China and East Africa, collected via an anonymous online questionnaire and deposited in a public repository accompanying a peer-reviewed comparative study (Ji et al., 2026). Consistent with the reviewer's request for transparency about instrument origin, the original questionnaire, titled "Virtual Reality in Augmenting Teaching of Life Sciences," was designed to assess VR awareness and adoption prospects specifically in practical, laboratory, and experimental teaching contexts across selected higher-learning institutions in China, Kenya, Uganda, and Tanzania; several items reference practical sessions, teaching aids, and experimental classes rather than classroom instruction in general. This origin is disclosed here because it bears directly on construct interpretation: one Perceived Usefulness item (PU2, "Do you have easy access to all necessary equipment and reagents for your experimental or practical sessions?") measures laboratory resource access rather than a belief about VR's usefulness as such, and one item (PU3) is a frequency-format question about the use of teaching aids rather than an agreement-format belief statement. This is a genuine limitation of the instrument as applied to a general VR-acceptance construct, is not resolvable through re-analysis, and is carried forward into the interpretation of the Perceived Usefulness results in Section 4 and the limitations discussed in Section 5. No independent psychometric validation report (for example, confirmatory factor analysis, pilot testing, or an index of item-objective congruence) accompanies the publicly deposited instrument; the composite reliability, average variance extracted, and discriminant validity statistics reported in Section 4.2 were therefore computed directly from the raw data by the present authors, rather than drawn from a pre-existing validation study, and are reported as such.

The full dataset comprises 339 valid responses. The analytic sample was restricted to respondents coded as Chinese undergraduate students (Region = China, Identity = Student), yielding a final analytic sample of 150 participants. Regarding the representativeness and adequacy of this subsample, three points are relevant. First, the $n = 150$ subsample was not independently drawn but represents the complete set of Chinese undergraduate respondents available within the public dataset; no further sampling decision was made by the present authors beyond this filtering criterion, which is fully reported in Section 3.4. Second, a post hoc power analysis for the regression model reported in Section 4.5 (four predictors, observed $R^2 = .320$) indicates statistical power exceeding .99 at $\alpha = .05$, meaning the sample was more than adequately powered to detect the observed effect sizes; the sample is comparable in size to related published TAM-based needs-assessment studies in this literature. Third, because the original respondents were not sampled with reference to CI coursework or CI-relevant disciplinary background, generalization from this sample to the population of undergraduate students specifically enrolled in, or targeted by, CI curricula should be made cautiously; this limitation is discussed further in Section 5. This sample spans thirteen academic disciplines, with the largest concentrations in Economics (n = 41, 27.3%), Management (n = 26, 17.3%), Science (n = 21, 14.0%), and Engineering (n = 20, 13.3%), and smaller representations from Literature, Law, Pedagogy, Philosophy, Medicine, Arts, Military Science, Agriculture, and History. Of the 150 participants, 106 (70.7%) reported prior experience using VR technology, and 44 (29.3%) reported no prior VR experience.

3.3 Instrument

The questionnaire operationalized five constructs drawn from the extended Technology Acceptance Model: Perceived Usefulness (three items, PU1–PU3), Perceived Ease of Use (three items, PEoU1–PEoU3), Innovativeness (two items, IN1–IN2), Attitude Toward Using (three items, AT1–AT3), and Behavioral Intention (two items, BI1–BI2), for a total of thirteen items, each rated on five-point scales. Table 2 summarizes the theoretical foundation, item count, scale, role in the acceptance model, and relationship of each construct to the Sustainable Competitive Intelligence framework in Table 1, as recommended to improve methodological transparency.

Table 2. Construct Operationalization Summary

Construct	Theoretical Foundation	Items	Measurement Scale	Role in the Model	Relationship to the SCI Framework
Perceived Usefulness (PU)	TAM (Davis, 1989)	3	5-point Likert (2 agreement items; 1 frequency-format item, see §3.2)	Antecedent of Attitude and Behavioral Intention	Indicates whether learners perceive VR as valuable, prior to any CI-specific implementation
Perceived Ease of Use (PEoU)	TAM (Davis, 1989)	3	5-point Likert (agree-disagree)	Antecedent of Attitude and Behavioral Intention	Establishes the baseline usability requirement for VR-CI delivery
Innovativeness (IN)	Extended TAM (Sagnier et al., 2020; Jang et al., 2021)	2	5-point Likert	Direct and indirect predictor of Behavioral Intention	Indicates disposition toward exploratory engagement, relevant to the CI cycle's Active Experimentation stage
Attitude Toward Using (AT)	TAM (Davis, 1989)	3	5-point Likert (agree-disagree)	Mediator between PU/PEoU and Behavioral Intention	Signals overall receptivity to VR-based CI instruction
Behavioral Intention (BI)	TAM (Davis, 1989)	2	5-point Likert (agree-disagree)	Outcome (dependent) variable	Proxy for likely uptake of a future VR-CI intervention; not a CI competency measure

Source: Elaborated by the authors.

As Table 2 makes explicit, none of the five TAM constructs directly operationalizes a CI competency; their role in the model is limited to establishing the acceptance-related preconditions under which a future CI-specific VR intervention could be delivered, consistent with the distinction drawn in Sections 2.4 and 2.5.

3.4 Data preparation and sensitivity analysis of the reverse-coding decision

The dataset codebook flags four items, PU1, PEoU3, BI1, and BI2, as administered with a reversed anchor order relative to the remaining nine items. Because this coding decision affects every downstream statistic, it is treated here as a matter requiring documentary evidence rather than statistical convenience alone. Examination of the original questionnaire wording, retrieved from the public data repository, shows that all four flagged items are negatively worded: PU1 asks whether VR "CANNOT increase memory power and knowledge retention"; PEoU3 asks whether it is "NOT EASY" to use VR; and BI1 and BI2 ask whether the respondent "WOULD NOT recommend" VR-based tools to colleagues or institutions. In each case, agreement with the negatively worded statement (a low raw score, given the reversed anchor) corresponds to a negative underlying belief, while disagreement (a high raw score) corresponds to a positive underlying belief, exactly matching the direction of the nine positively worded items on which agreement (a high raw score) already signals a positive belief. The double negation created by pairing negatively worded items with a reversed anchor is, on inspection, self-canceling: it produces raw scores that are already oriented in the same direction as the rest of the scale, without a numerical transformation being applied.

This documentary evidence is consistent with, and explains, the empirical pattern reported in the earlier version of this manuscript, and it follows methodological guidance that reverse-coded Likert items be verified empirically, rather than assumed from codebook metadata alone, before being combined into composite scores (Kusmaryono, Wijayanti, & Maharani, 2022). Table 3 reports the full sensitivity analysis requested by the reviewers, comparing internal consistency and regression results under both coding decisions.

Table 3. Sensitivity Analysis: Raw versus Codebook-Reversed Item Coding

Statistic	Raw (Unreversed) Coding — Used in This Paper	Codebook-Reversed Coding
Cronbach's alpha — PU	0.834	-0.803
Cronbach's alpha — PEoU	0.665	-0.974
Cronbach's alpha — IN	0.413	0.413
Cronbach's alpha — AT	0.493	0.493
Cronbach's alpha — BI	0.622	0.622
Regression R^2 (BI outcome)	0.320	0.249
Regression F(4,145)	17.07	12.00
Attitude coefficient (β, p)	+0.30, p<.001	−0.61, p<.001
Innovativeness coefficient (β, p)	+0.18, p=.013	−0.32, p=.011

Source: Elaborated by the authors. See §3.4 for the documentary evidence supporting the raw-coding decision.

As Table 3 shows, applying the codebook reversal produces a negative reliability coefficient for the Perceived Usefulness and Perceived Ease of Use scales, indicating an internally incoherent measurement model, because only one of the three items in each of these two constructs is flagged, while the other two are not; reversing a single item against two unreversed items necessarily inverts its correlation with the rest of the scale. The Innovativeness, Attitude, and Behavioral Intention alphas are unaffected by the coding decision reported in Table 3, because Behavioral Intention's two items are both flagged and are therefore reversed together, which preserves their relative correlation, while Innovativeness and Attitude contain no flagged items at all. When the reversed coding is instead carried through to the regression model, the sign of the Attitude and Innovativeness coefficients inverts and the model's explained variance falls from $R^2 = .320$ to $R^2 = .249$, because reversing both Behavioral Intention items flips the direction of the dependent variable itself. Raw coding was retained for all analyses reported in Section 4 because it is the only one of the two coding decisions that produces an internally consistent measurement model, a result confirmed by the composite reliability and average variance extracted statistics in Section 4.2, and because it is directly supported by the negatively worded item text documented above. This decision, and the evidence supporting it, is reported in full here so that it is independently auditable rather than presented as a bare assertion.

3.5 Data analysis

The Python libraries utilized included pandas, NumPy, SciPy, statsmodels and scikit-learn. Using a conventional five-band scale, as found in similar needs-assessment survey research (Choi & Park, 2024), descriptive statistics were calculated at the item level and interpreted accordingly; the ranked discrepancy model, which has been suggested as a methodological alternative to mean-based scoring of non-normally distributed ordinal needs-assessment data (Choi & Park, 2023), is mentioned only as a direction for future research and is not used in the present analysis. Internal consistency was evaluated by Cronbach's alpha for each construct and for the 13 items total, as well as computed composite reliability (CR) from single factor loadings obtained for each construct through principal component analysis, and average variance extracted (AVE) was calculated for each construct, and discriminant validity was evaluated by the Fornell–Larcker criterion, where the square root of each construct's AVE was compared with its correlations with the remaining four constructs. Five construct-level composite scores were used to calculate Pearson correlations between the scores. A multiple regression analysis to predict Behavioral Intention from Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using and Innovativeness was estimated using ordinary least squares (OLS) regression method. In addition to the variance inflation factors reported in the previous version of this manuscript, the regression was tested for normality of the residuals (the Shapiro–Wilk test), heteroscedasticity (the Breusch–Pagan test), independence of the residuals (the Durbin–Watson statistic), and influential observations (Cook's distance); HC3 robust standard errors were also computed as a robustness check. Independent-samples t-tests (Welch correction for unequal variances) were used to determine whether there were significant differences in construct scores between students with and without previous VR experience, and between students in STEM disciplines (Science, Engineering, Agriculture, Medicine) and students in humanities and social science disciplines. The 0.05 level of significance was adopted for all significance tests and full diagnostic results are presented in Section 4.5. This analytical process is summarized in Figure 2 from the initial public data to the design parameters linked to acceptance that are used in the framework in Table 1.

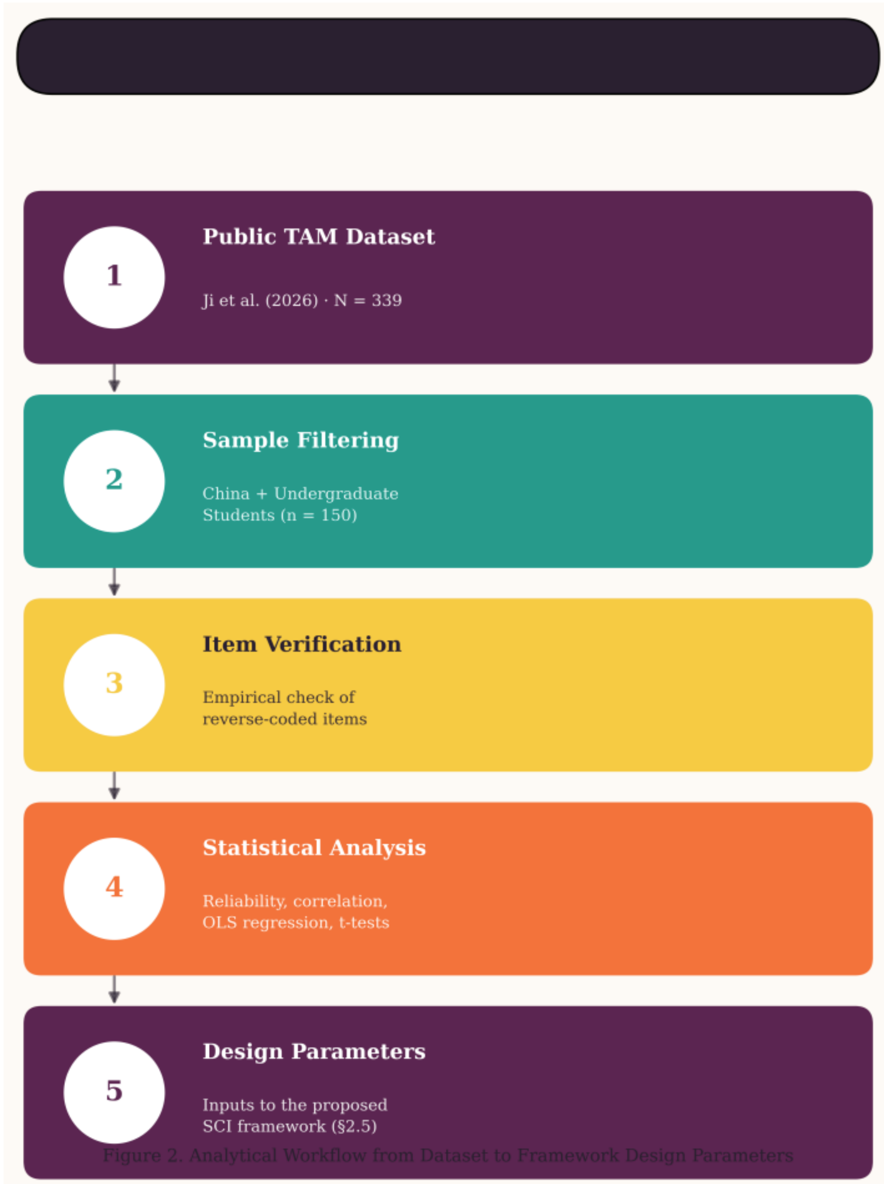

Figure 2. Analytical Workflow from Dataset to Framework Design Parameters

Source: Elaborated by the authors.

4 RESULTS AND DISCUSSION

The analysis below characterizes the technology acceptance profile of the sampled Chinese undergraduate population. Consistent with Sections 2.4 and 3, these results are interpreted as evidence about VR acceptance, which bears on the feasibility of delivering the framework in Table 1, and not as evidence about Competitive Intelligence competency, which the present dataset does not measure. Subsections are structured to answer, in sequence, the study's empirical objectives before returning, in Section 4.7, to the implications for the CI cycle specifically.

4.1 Sample profile

Table 4. Sample Profile: Disciplinary Composition and Prior VR Experience (N = 150)

Discipline	n	%
Economics	41	27.3%
Management	26	17.3%
Science	21	14%
Engineering	20	13.3%
Literature	12	8%
Law	10	6.7%
Pedagogy	8	5.3%
Philosophy	4	2.7%
Medicine	3	2%
Arts	2	1.3%
Military Science	1	0.7%
Agriculture	1	0.7%
History	1	0.7%
Prior VR Experience	**n**	**%**
Prior VR experience	106	70.7%
No prior VR experience	44	29.3%

Source: Elaborated by the authors from Ji et al. (2026) dataset.

Table 4 summarizes the disciplinary composition and prior VR exposure of the analytic sample (N = 150). Business-adjacent disciplines (Economics and Management) together account for approximately 45% of the sample, which is the population most directly relevant to a CI curriculum, although the sample was not drawn with reference to CI coursework enrollment specifically, a limitation noted in Section 3.2. The majority of participants (70.7%) had prior hands-on experience with VR technology, indicating that, within this population, VR is no longer a wholly unfamiliar medium, a condition that shapes the interpretation of the acceptance results reported below.

4.2 Reliability, composite reliability, and discriminant validity

Table 5. Internal Consistency, Composite Reliability, and Average Variance Extracted by Construct

Construct	Items	Cronbach's α	Composite Reliability (CR)	AVE
PU	3	0.834	0.900	0.751
PEoU	3	0.665	0.820	0.604
IN	2	0.413	0.774	0.631
AT	3	0.493	0.749	0.502
BI	2	0.622	0.842	0.727
Overall (13 items)	13	0.740	—	—

Source: Elaborated by the authors. CR ≥ .70 and AVE ≥ .50 conventionally indicate adequate convergent reliability.

As shown in Table 5, the retained thirteen-item instrument demonstrated acceptable overall internal consistency (α = .74). Cronbach's alpha was good for Perceived Usefulness (α = .83) and acceptable for Perceived Ease of Use (α = .67) and Behavioral Intention (α = .62); the two-item Innovativeness (α = .41) and three-item Attitude (α = .49) scales fell below conventional alpha thresholds, a limitation the reviewers correctly identified as requiring deeper treatment than the earlier version of this manuscript provided. Because alpha is mechanically sensitive to the number of items in a scale and does not itself establish convergent validity, composite reliability (CR) and average variance extracted (AVE) were computed for all five constructs. Every construct met the conventional CR threshold of .70 (PU = .90, PEoU = .82, IN = .77, AT = .75, BI = .84) and the conventional AVE threshold of .50 (PU = .75, PEoU = .60, IN = .63, AT = .50, BI = .73), indicating that, notwithstanding the low alpha values for Innovativeness and Attitude, each construct's items share substantially more variance with their intended construct than with measurement error. The Fornell–Larcker criterion was satisfied for all five constructs: the square root of each construct's AVE exceeded its largest correlation with any other construct (for example, √AVE for Attitude = .71 against a maximum inter-construct correlation of .46), supporting discriminant validity across the five-construct model. These additional statistics do not eliminate the Innovativeness and Attitude reliability concern, and results involving these two constructs continue to be interpreted with corresponding caution throughout this section, but they show that the concern is specifically about alpha's sensitivity to short scales rather than about the constructs' convergent or discriminant validity.

4.3 Item-level needs assessment

Table 6. Item-Level Descriptive Statistics and Needs Assessment (N = 150)

Item	Description	M	SD	Level
Perceived Usefulness				
PU1	VR would improve my learning performance in coursework	3.41	0.93	Moderate
PU2	VR would make it easier to understand complex course content	3.25	0.96	Moderate
PU3	Overall, I find VR useful for my learning	3.13	1.00	Moderate
Construct mean		3.26	0.84	Moderate
Perceived Ease of Use				
PEoU1	Learning to operate VR equipment would be easy for me	3.33	1.02	Moderate
PEoU2	Interacting with VR learning environments is clear and understandable	3.05	0.93	Moderate
PEoU3	I would find VR easy to use for coursework	3.19	0.90	Moderate
Construct mean		3.19	0.74	Moderate
Innovativeness				
IN1	I like to try out new technologies before my peers	4.12	0.66	Agree
IN2	I am generally among the first to experiment with new technology	4.05	0.58	Agree
Construct mean		4.08	0.50	Agree
Attitude Toward Using				
AT1	Using VR for learning is a good idea	4.13	0.73	Agree
AT2	I have a positive attitude toward using VR in my courses	3.68	0.79	Agree
AT3	Learning with VR would be an enjoyable experience	3.73	0.78	Agree
Construct mean		3.85	0.54	Agree

Item	Description	M	SD	Level
Behavioral Intention				
BI1	I intend to use VR for learning in the future	3.58	0.98	Agree
BI2	I plan to use VR-based learning tools when available	3.69	0.90	Agree
Construct mean		3.64	0.80	Agree

Source: Elaborated by the authors. Level bands follow Choi and Park (2024): 4.50–5.00 strongly agree; 3.50–4.49 agree; 2.50–3.49 moderate; 1.50–2.49 disagree; 1.00–1.49 strongly disagree.

Table 6 presents the mean and standard deviation for each of the thirteen items, grouped by TAM construct; the Perceived Usefulness items in Table 6 should be read in light of the instrument-origin limitation reported in Section 3.2, since PU2 and PU3 do not share the agreement-based response format of the remaining items. Two patterns are noteworthy. First, Innovativeness and Attitude items received the highest mean ratings (construct means of 4.08 and 3.85, respectively, both in the "agree" band), indicating that Chinese undergraduate students in this sample are, in general, favorably disposed toward experimenting with new technologies such as VR and hold generally positive attitudes toward its educational use. Second, Perceived Usefulness (M = 3.26) and Perceived Ease of Use (M = 3.19) fell in the "moderate" band, close to the scale midpoint. Behavioral Intention (M = 3.64) fell in the "agree" band but with a comparatively wide standard deviation (SD = 0.80), suggesting meaningful heterogeneity in willingness to use VR across the sample. Figure 3 displays these construct-level means with their associated standard deviations, while Figure 4 disaggregates the same data to the item level.

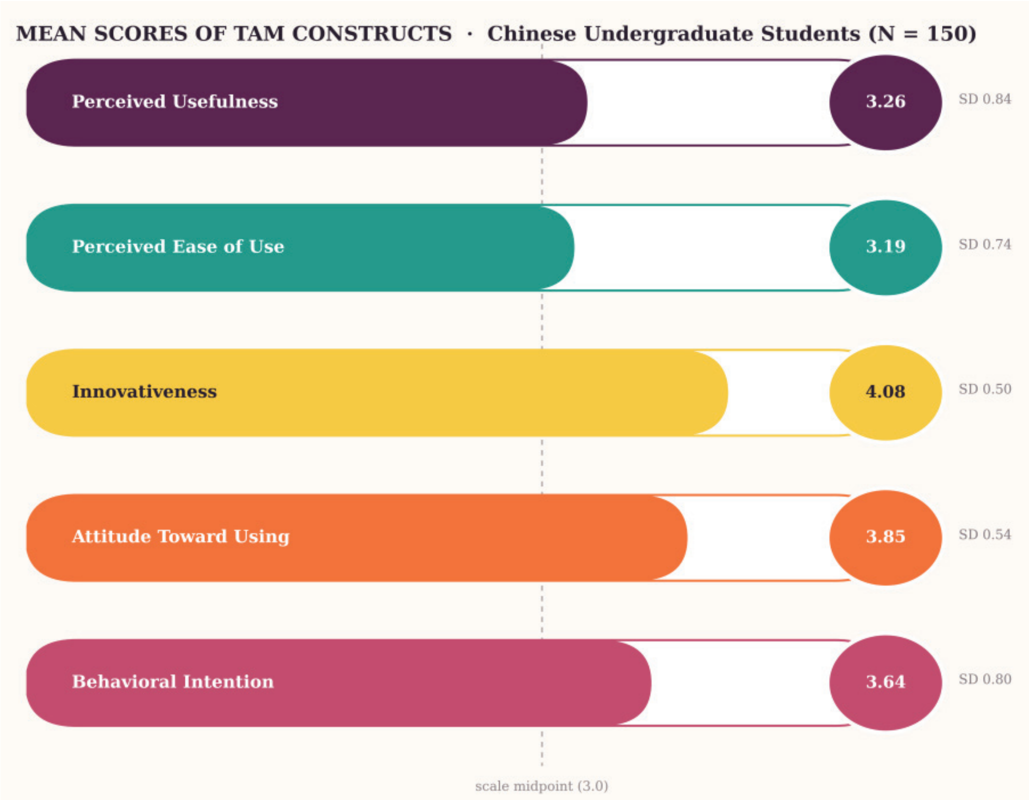

Figure 3. Mean Scores of TAM Constructs Among Chinese Undergraduate Students (N = 150)

Source: Elaborated by the authors.

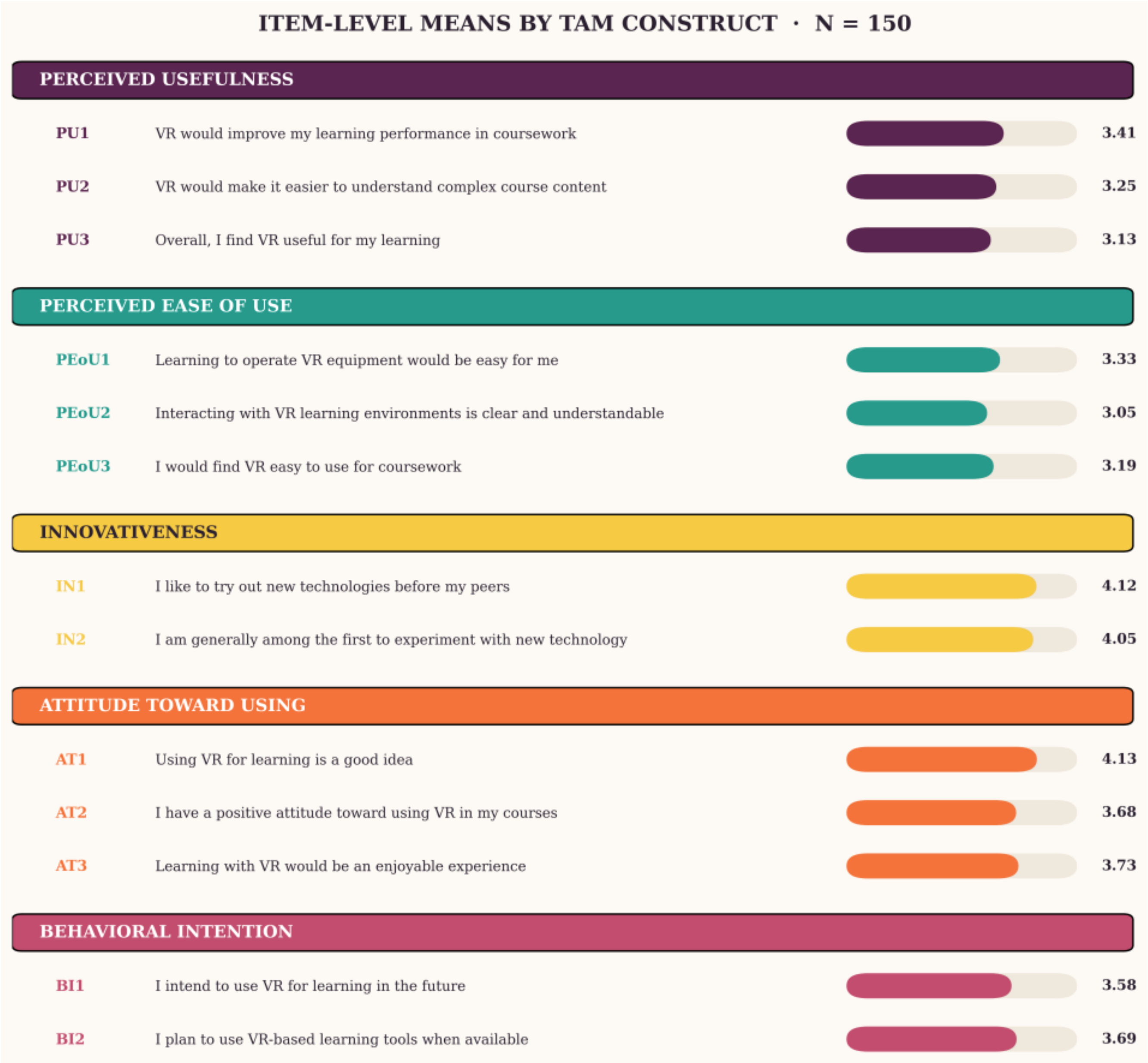

Figure 4. Item-Level Means by TAM Construct (N = 150)

Source: Elaborated by the authors.

None of these patterns describes CI-relevant behavior; they describe general beliefs about an educational technology, and are reported here strictly as inputs to the acceptance-pathway component of the framework in Table 1, not as findings about environmental scanning, analysis, or any other CI competency.

4.4 Relationships among tam constructs

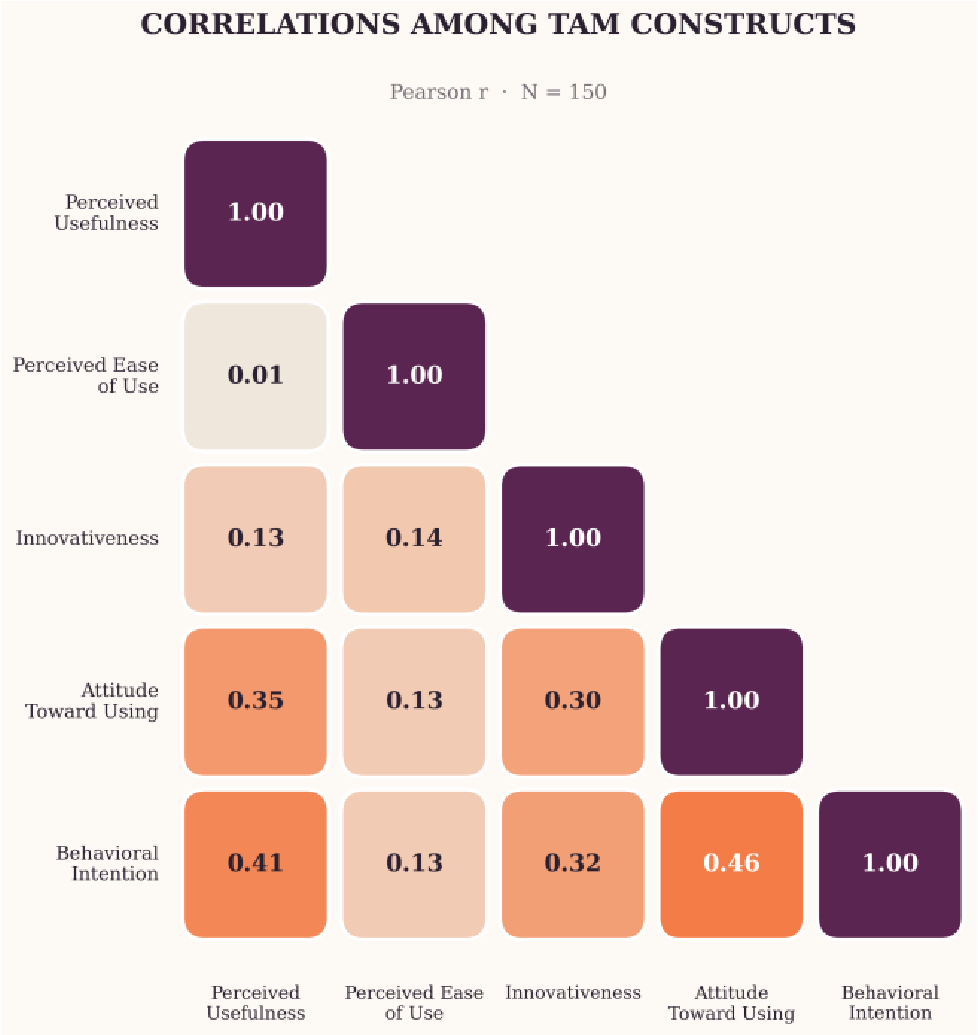

Figure 5. Pearson Correlations Among TAM Construct Scores (N = 150)

Source: Elaborated by the authors. Lower-triangular heatmap; cell values are Pearson r.

Figure 5 reports Pearson correlations among the five construct-level composite scores as a correlation heatmap. All correlations were positive and in the directions anticipated by TAM theory. Attitude Toward Using correlated most strongly with Behavioral Intention (r = .46), followed by Perceived Usefulness (r = .41) and Innovativeness (r = .32). Perceived Ease of Use showed comparatively weak associations with the other constructs, including Behavioral Intention (r = .13). Perceived Usefulness and Attitude were moderately correlated (r = .35), consistent with the TAM pathway in which usefulness beliefs shape overall attitude. All correlations remained below the discriminant-validity thresholds established in Section 4.2, indicating that the five constructs, while related as TAM theory predicts, remain empirically distinguishable from one another.

4.5 Predictors of behavioral intention and regression diagnostics

Table 7. OLS Regression Predicting Behavioral Intention

Predictor	B	SE	β	t	p
(Constant)	-0.375	0.555	—	-0.675	0.501
Perceived Usefulness	0.275	0.070	0.287	3.921	<.001
Perceived Ease of Use	0.069	0.076	0.064	0.915	0.362
Attitude Toward Using	0.440	0.113	0.296	3.880	<.001
Innovativeness	0.293	0.117	0.181	2.509	0.013

Note. $R^2 = 0.32$, Adjusted $R^2 = 0.301$, $F(4, 145) = 17.07$, $p < .001$. Coefficients remained significant using heteroscedasticity-robust (HC3) standard errors (see §3.5, §4.5).
Source: Elaborated by the authors.

An ordinary least squares regression predicting Behavioral Intention from Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Innovativeness was statistically significant, $F(4, 145) = 17.07$, $p < .001$, and explained approximately 32% of the variance in Behavioral Intention ($R^2 = .32$, adjusted $R^2 = .30$). As shown in Table 7 and Figure 6, Attitude Toward Using was the strongest predictor ($\beta = .30$, $p < .001$), followed by Perceived Usefulness ($\beta = .29$, $p < .001$) and Innovativeness ($\beta = .18$, $p = .013$). Perceived Ease of Use was not a statistically significant predictor once the other three constructs were accounted for ($\beta = .06$, $p = .362$).

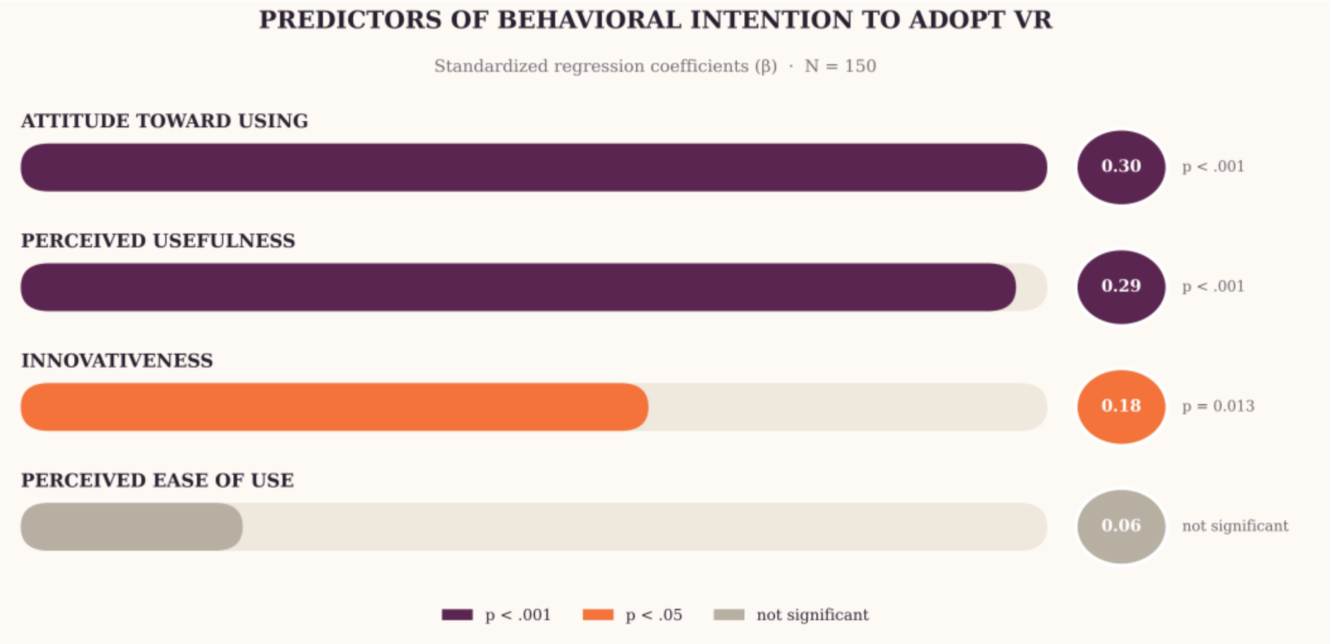

Figure 6. Predictors of Behavioral Intention to Adopt VR (N = 150)

Source: Elaborated by the authors.

Responding to the reviewers' request for a complete assumption check, four additional diagnostics were run. Variance inflation factors for all predictors were below 1.3, indicating no problematic multicollinearity. The Durbin–Watson statistic (2.06) indicated no meaningful autocorrelation among residuals. The Breusch–Pagan test was not significant (LM = 4.23, p = .376), indicating that the assumption of homoscedasticity was not violated. The Shapiro–Wilk test indicated that residuals departed significantly from normality (W = .94, p < .001), with a negative skew (−0.88) consistent with the bounded, ceiling-influenced nature of Likert-based composite scores; because OLS coefficient estimates remain unbiased under non-normality and only formal inference is affected, the regression was re-estimated using heteroscedasticity-and-non-normality-robust (HC3) standard errors, which produced materially identical conclusions (Perceived Usefulness p = .001, Attitude p < .001, Innovativeness p = .022, Perceived Ease of Use p = .440). Cook's distance identified eleven observations (7.3% of the sample) exceeding the conventional 4/n threshold, with a maximum value of .127, well below the value of 1.0 conventionally treated as indicating a highly influential case; no single observation was judged to be distorting the reported coefficients. These diagnostics are reported in full so that the robustness of the regression model, rather than only its point estimates, is available for evaluation.

4.6 Prior vr exposure and disciplinary differences

Table 8. Group Comparisons by Prior VR Experience and Discipline

PANEL A. BY PRIOR VR EXPERIENCE PANEL A. BY PRIOR VR EXPERIENCE				
Construct	**Prior VR (M)**	**No Prior VR (M)**	**t**	**p**
Perceived Usefulness	3.21	3.40	-1.38	0.17
Perceived Ease of Use	3.35	2.81	4.20	<.001
Innovativeness	4.11	4.02	0.95	0.343
Attitude Toward Using	3.83	3.88	-0.52	0.604
Behavioral Intention	3.56	3.83	-2.20	0.03
PANEL B. BY DISCIPLINARY CLUSTER				
Construct	**STEM (M)**	**Humanities/Social (M)**	**t**	**p**
Perceived Usefulness	3.29	3.25	0.23	0.816
Perceived Ease of Use	3.06	3.24	-1.43	0.157
Innovativeness	4.24	4.01	2.70	0.008
Attitude Toward Using	4.03	3.77	2.92	0.004
Behavioral Intention	3.78	3.58	1.52	0.133

Source: Elaborated by the authors. Welch t-test used throughout.

Table 8 reports group comparisons by prior VR experience and by disciplinary cluster. Students with prior VR experience reported significantly higher Perceived Ease of Use than those without prior experience (M = 3.35 vs. M = 2.81; t(85.4) = 4.20, p < .001), which is unsurprising, since direct familiarity with a technology typically reduces perceived operational effort. Counterintuitively, students with prior VR experience reported significantly lower Behavioral Intention than inexperienced students

($M = 3.56$ vs. $M = 3.83$; $t(73.6) = -2.20$, $p = .030$). No significant differences by prior experience emerged for Perceived Usefulness, Attitude, or Innovativeness. This pattern is consistent with a novelty-recession effect documented elsewhere in the immersive-technology literature, in which initial enthusiasm among first-time users is not always sustained once the technology becomes familiar (Bower, DeWitt, & Lai, 2020).

Disciplinary comparisons showed that STEM students (Science, Engineering, Agriculture, Medicine; $n = 45$) reported significantly higher Attitude Toward Using ($M = 4.03$ vs. $M = 3.77$; $t(76.9) = 2.92$, $p = .004$) and Innovativeness ($M = 4.24$ vs. $M = 4.01$; $t(85.2) = 2.70$, $p = .008$) than humanities and social science students ($n = 105$), with no significant difference in Behavioral Intention itself ($p = .133$). Because Economics and Management students, the population most directly relevant to CI curricula, are classified here within the humanities and social science cluster, this result suggests that acceptance-building efforts for a VR-based SCI curriculum embedded in business programs may need greater investment in cultivating positive attitude and innovativeness among target learners than an equivalent intervention in a STEM curriculum would require, even though the two groups did not differ significantly in ultimate behavioral intention.

4.7 Implications for the ci cycle and the proposed framework

The results in Sections 4.1 through 4.6 refine three acceptance-related design parameters of the framework in Table 1, and each is stated here strictly at the level the data support. First, because Attitude and Perceived Usefulness, rather than Perceived Ease of Use, are the dominant predictors of Behavioral Intention in this population, the acceptance pathway preceding the Concrete Experience stage in Table 1 should foreground demonstrable usefulness, for example by opening each VR-CI module with a concrete illustration of the scanning or analytical task the simulation supports, rather than investing disproportionate effort in interface simplification. Second, because Innovativeness predicted Behavioral Intention independently of Attitude and Usefulness, the reflective and governance stage of the framework, corresponding to the CI cycle's feedback loop, should be designed to reward exploratory, non-routine scanning and analytical strategies during active experimentation, capitalizing on students' generally high disposition toward technological experimentation. Third, because prior VR experience was associated with lower, not higher, behavioral intention, the framework's pedagogical value cannot depend on the sustained novelty of the VR medium; consistent with the Cognitive Affective Model of Immersive Learning (Makransky & Petersen, 2021), it must be renewed through the deliberate reflective and governance stages mapped in Table 1, corresponding to the CI cycle's own feedback mechanism, rather than through the VR experience in isolation.

These are acceptance-related design parameters for the technology through which the framework in Table 1 would be delivered. They are not evidence that the framework develops environmental scanning literacy, analytical rigour, dissemination judgment, or any other CI-specific competency, and this paper does not present them as such. Whether a VR-based CI simulation, structured according to Table 1, actually develops the CI competencies it targets is an empirical question that remains open and is identified as the priority for future research in Section 5.

5 FINAL CONSIDERATIONS

This paper framed Competitive Intelligence in its complete life cycle as the epistemological axis of a framework for Sustainable Competitive Intelligence (SCI) experiential learning as a conceptual matrix where every phase of the CI cycle was associated with a specific VR-experiential learning mechanism, a specific CI competency and an expected future indicator. It empirically grounded the design parameters related to acceptance in the aforementioned framework with factors obtained through a needs assessment of the technology acceptance pattern of 150 Chinese undergraduate students in the context of VR-based learning. Attitude Toward Using and Perceived Usefulness were the top two predictors of Behavioral Intention to adopt VR (R^2 = .32, robust to heteroscedasticity-consistent standard errors), with Perceived Ease of Use not being a significant independent predictor, and prior VR experience was associated with higher perceived ease of use but lower behavioral intention; and STEM students reported significantly higher attitude and innovativeness than their humanities and social science counterparts.

As the reviewers rightly requested, it is essential to make clear what this study shows and doesn't show. It shows that Chinese undergraduate students generally welcome VR as an educational tool, even students in business-related fields most closely related to the CI curriculum, and highlights the beliefs that have the most significant influence on their acceptance of VR. It does not show that the teaching of Competitive Intelligence through VR-based instruction can be improved in teaching and learning content, learner motivation, and learning efficiency, or that students who accept the VR technology can be better equipped to learn tasks of environmental scanning, analysis, dissemination, or governance. This framework, therefore, is presented here and throughout this paper with the word proposed and is empirically supported by the acceptance results presented in Section 4, not validated by a study of the empirically tested development of Sustainable Competitive Intelligence. Implementing this framework in a real-life CI course, that is, measuring the CI-specific indicators mentioned in the last column of Table 1, is not a mere truism; it is the major focus for future research to close this gap.

The study is a contribution to the literature in three ways. First, it expands the literature on CI education, which has provided few empirical demonstrations of the design of immersive courses, by offering a CI explicit and mechanistically linked to the stages of the CI cycle, the view on dynamic capabilities, and organizational learning as an educational-technology study, rather than as a general term for an educational-technology study. Secondly, it shows the methodological transparency of the needs-assessment research practiced in a situation with a limited amount of data, revealing the authoring context of the instrument, a methodological constraint of construct-validity at item level, which is found during the process, and a thorough sensitivity analysis of the coding decisions made, including documentary evidence of the origin of the items. Third, it provides composite reliability, average variance extracted, discriminant validity and a full OLS diagnostic battery in addition to the original regression results, as requested by the reviewers for a more thorough evaluation of the measurement and inferential model.

There are some limitations which should guide further research beyond the above mentioned. Both limitations restricted the interpretation of the results of Perceived Usefulness specifically, as it measured general VR acceptance instead of acceptance of a CI-specific application, and one of the Perceived Usefulness items measured laboratory resource access instead of a belief in VR. Due to the cross-sectional design of the study, causal relationships cannot be inferred from the results, and the sample was well powered and representative of the available respondents in the source dataset for undergraduate students in China, but it was not selected based on CI coursework enrollment and should not be generalized to CI-enrolled populations without further research. However, the internal consistency of the subscales of the Innovativeness and Attitude was below the recommended cutpoints, and composite reliability and AVE partially compensated for this but not fully. Future studies should focus on the direct application of the framework in Table 1 in a real classroom-based undergraduate CI course with the CI-specific indicators provided in the table, rather than a general technology acceptance measurement, and pre- and post-tests for analytical and scanning competency should be used instead of technology acceptance. The ranked discrepancy model is mentioned as a methodological complement to the mean-based scoring adopted in this research (Choi & Park, 2023). Studies based on a complete academic year of longitudinal data would also help to determine whether the novelty-recession effect found here continues as students become more experienced with CI-specific VR content.

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Author contributions: Conceptualization: Xucheng Zhou and Sirirat Petsangsri; data source identification and curation: Xucheng Zhou and Sirirat Petsangsri; formal analysis and interpretation: Xucheng Zhou; writing–original draft: Xucheng Zhou; writing–review and editing: Sirirat Petsangsri and Thanin Ratanaolarn; supervision: Thanin Ratanaolarn. All authors have read and agreed to the final version of the manuscript.

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