



Examining Transformational Leadership Among Undergraduate Faculty Using a Competitive Intelligence Framework

Examinando a Liderança Transformacional entre Docentes de Graduação Utilizando um Framework de Inteligência Competitiva

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ABSTRACT | Purpose: This study develops a competitive intelligence framework for examining transformational leadership among faculty teaching undergraduate programmes in Chinese universities. It asks how information acquisition, analysis, dissemination, and utilization can be linked with idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. **Methodology/ approach:** The article adopts a cross-sectional, faculty-level research design. It specifies an integrated measurement model and proposes a reproducible analytical sequence covering data screening, descriptive analysis, reliability, convergent and discriminant validity, correlation analysis, multivariable modelling, and robustness checks. Because field-collected responses were unavailable, the study is presented as an analysis-ready methodological design rather than population-level empirical evidence. **Originality/ Relevance:** The study connects the competitive intelligence cycle with transformational leadership in undergraduate education, shifting competitive intelligence from an institutional monitoring function to a leadership-support mechanism. **Key findings:** The framework identifies intelligence utilization and dissemination as direct pathways through which strategic information may inform faculty-oriented leadership. It also shows that leadership should be assessed as a multidimensional construct rather than a single managerial trait. **Theoretical/methodological contributions:** The article offers an integrated construct map, transparent variable architecture, and testable model for rigorous faculty surveys in Chinese higher education.

Keywords | Competitive intelligence. Transformational leadership. Undergraduate faculty. Chinese universities. Information utilization. Higher education leadership

RESUMO | Objetivo: Este estudo desenvolve um framework de Inteligência Competitiva para examinar a liderança transformacional entre docentes que atuam em cursos de graduação em universidades chinesas. O estudo investiga como a aquisição, análise, disseminação e utilização de informações podem estar relacionadas à influência idealizada, motivação inspiradora, estimulação intelectual e consideração individualizada. **Metodologia/Abordagem:** O artigo adota um desenho de pesquisa transversal em nível docente. Especifica um modelo integrado de mensuração e propõe uma sequência analítica reproduzível que abrange triagem dos dados, análise descritiva, confiabilidade, validade convergente e discriminante, análise de correlação, modelagem multivariada e testes de robustez. Como não estavam disponíveis respostas coletadas em campo, o estudo é apresentado como um desenho metodológico pronto para análise, e não como evidência empírica em nível populacional. **Originalidade/Relevância:** O estudo conecta o ciclo de Inteligência Competitiva à liderança transformacional na educação de graduação, reposicionando a Inteligência Competitiva de uma função de monitoramento institucional para um mecanismo de suporte à liderança. **Principais Resultados:** O framework identifica a utilização e a disseminação da inteligência como vias diretas pelas quais informações estratégicas podem subsidiar a liderança voltada aos docentes. O estudo também demonstra que a liderança deve ser avaliada como um construto multidimensional, e não como um único atributo gerencial. **Contribuições Teóricas/Metodológicas:** O artigo apresenta um mapa integrado de construtos, uma arquitetura transparente de variáveis e um modelo testável para a realização de pesquisas rigorosas com docentes no contexto do ensino superior chinês.

Palavras-chave | Inteligência Competitiva. Liderança transformacional. Docentes de graduação. Universidades chinesas. Utilização da informação. Liderança no ensino superior.

1. INTRODUCTION

The Landscape of undergraduate teaching has been transformed, with the decisions made in universities now occurring in a context of policy change, digital platforms, new assessment methods, changing labour-market expectations and increased public scrutiny. These pressures are faced by faculty members in curriculum committees, programme reviews, student-support work, quality assurance, and in the classroom. It's not just the lack of information. It is the discrepancy in the information-giving power to decide what's important, to test the credibility of the information, to interpret the meaning of the information, to share it with those who need it, and to use the information in time to make a decision. Competitive intelligence is a structured vocabulary for that process.

Competitive intelligence is a term typically used for firms and markets but the essence of the concept is more general. It's about ethics and systematic transformation of fragmentary signals into usable knowledge to make decisions. Recent studies on intelligence suggest that it is a combination of components: the ability to scan the environment, interpret it analytically, disseminate it, use it, and feedback (Cavallo et al., 2021; Madureira et al., 2023; Maungwa & Laughton, 2023). It can make a difference in college. A university can have very comprehensive dashboards and policy documents and not have a common process for making academic judgement.

The same distinction is also reflected in modern analysis research. Data resources are needed with interpretive routines, decision authority and adaptive action (Conboy et al., 2020; Dubey et al., 2020; Ghasemaghahi, 2021; Mikalef et al., 2020). The same is true for AI skills. To realize any value from technical assets, human intervention, coordination and organizational learning are required (Awamleh & Ertugan, 2021; Mikalef & Gupta, 2021). Competitive intelligence is therefore a suitable journal-based approach to the study of leadership in universities as it asks what questions need to be asked and how the attention must be organised and how evidence is transformed into purposeful action.



Transformational leadership is relevant to that conversion. It is defined by its four recognisable dimensions: allowing leaders to demonstrate trustworthy values, provide direction, offer intellectual stimulation and engage in personal development. Numerous recent empirical studies as well as a systematic review reveal that transformational leadership is associated with engagement, satisfaction, and psychological well-being (Agazu et al., 2025; Abolnasser et al., 2023) and with performance through motivational and organizational mechanisms. The results do not provide any information on the processes by which such leadership becomes credible. Indeed, previous research in the field of educational motivation also indicates that autonomy support, competence support and relatedness-supportive practice influence engagement and internalization, but these mechanisms are not assessed in the current workbook (Bureau et al., 2022; Reeve & Cheon, 2021; Ryan & Deci, 2020; Vansteenkiste et al., 2020). For instance, creating a compelling vision is challenging if it is not tied to policy evidence, student needs, developments at other institutions, or faculty expertise.

This relationship could also go the other way. Questioning and participation by leaders can help to establish stronger intelligence routines. When leadership is trusted, faculty will be more inclined to share weak signals, question inadequate evidence, and report difficulties in implementation. The present study thus does not consider competitive intelligence as a fact. It investigates whether the two constructs are associated in an analytically designed system. This warning is relevant, since it is not possible to determine a temporal sequence from cross-sectional perceptions even in the presence of stable coefficients. Throughout the analysis, therefore, the explicit associational language is used.

The future field test has a significant context in China. The digital world has seen significant growth and universities are under pressure to link education to technology and new skill requirements. As digital transformation is reviewed, academic work, governance, culture and capability building are involved in institutional change, apart from technology acquisition (Benavides et al., 2020; Kang & Xu, 2025). Similar trends regarding acceptance of AI tools, work performance, well-being, and teaching engagement have been found in studies of university educators in China, where work conditions and individual readiness are found to influence these aspects (Xu et al., 2023; Xu et al., 2024; Wei et al., 2025; Wen & Cai, 2025; Xiang et al., 2025). These research findings reinforce the importance of leadership that can understand and respond to external change, but is not driven to make it a mandatory project.

The research problem is when two works are mismatched. Competitive-intelligence research is an explanation of the processes of scanning, analysing, disseminating and using information in an organization. Transformational-leadership research seeks to understand how leaders affect meaning, motivation, learning and development. The evidence cited rarely measures both systems, as connected faculty perceived capabilities. Consequently, the information basis of transformational leadership is still not sufficiently specified, and leadership is frequently considered a missing social condition in an intelligence model.

This misalignment gives rise to 6 related gaps. The theoretical gap relates to the lack of an explanation of how intelligence routines could be linked to different leadership behaviours. The empirical gap is related to the lack of the simultaneous measurement of the four intelligence stages and four leadership dimensions among faculty. A methodological gap is the widespread use of only one estimator in organizational surveys, as well as insufficient attention being paid to common source bias (Jordan & Troth, 2020; Kock et al., 2021). The contextual gap is reflected in the requirement to translate the model

into the Chinese governance system language while not blindly adopting a transactional approach with the jargon of a company. The data deficiency is the lack of public field data directly measuring the entire framework. The practical problem here is one of identification of useful intelligence and information volume by the academic leaders without an auditable process.

The present article answers this question by an analytical demonstration in the form of a framework development and a simulation. The Faculty Profiles are the generated faculty profiles arranged around an institutional structure oriented towards China. It was developed for method testing, questionnaire development and analysis plan. Does not include answers from teachers. This boundary restricts the claims in this article. The numerical results can indicate if the designed structure is coherent and can be recovered in the proposed scoring and measurement checks and models. They can't quantify the conditions for leadership in China, can't recognize and select real institutions, or make policy decisions.

Inside the boundary, the goals of the study are threefold. First, it identifies educational competitive intelligence as an ability perceived by faculty that is comprised of 4 components: acquisition, analysis, dissemination, and utilization. Second, it ties that ability to idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. Third, it provides the workflow that can be audited, which is a union of measurement diagnostics, the grouping of explanatory models and sensitivity checks and the grouping of institutions in prediction. The conceptual framework is shown in Figure 1. Competitive intelligence is revisited as the organizing construct and transformational leadership is explored as the leadership pattern that relates to the quality of information conversion.

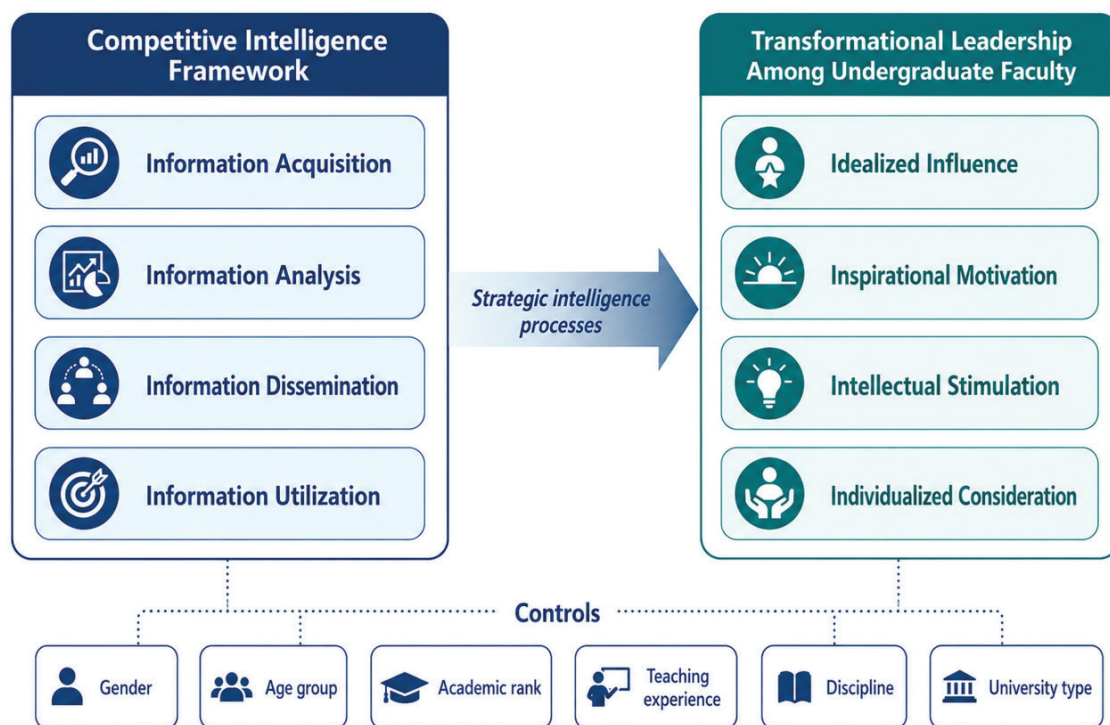


Figure 1. Conceptual framework linking competitive-intelligence acquisition, analysis, dissemination, and utilization with four dimensions of transformational leadership. Source: Author-developed framework.



2. THEORETICAL FRAMEWORK

2.1 Competitive intelligence as an organizational capability

The first step in competitive intelligence is to make a decision need. Information is transformed into intelligence through selection, evaluation, interpretation and correlation of the information with a potential response. Why this distinction is important has been identified through scanning the environment. There is both consolidation and fragmentation of organizations; they can choose to centralize scanning functions whilst information is fragmented across professional groups (Robinson et al., 2021). This is evident at universities. Different parts of the environment are observed by the policy offices, teaching centers, departments, libraries, career services, student affairs units, and faculty committees.

The first empirical dimension in the framework is acquisition. It brings in a systematic approach to higher education policy, teaching technologies, student needs, employer expectations, graduate skills and developments at similar institutions. Acquisition does not mean "unrestricted collection." A key aspect of open-source intelligence work is to identify sources, relevance, and mapping of the stakeholders involved (Lutz & Bodendorf, 2020). The collection in academic environments also needs to be restrained to be lawful and ethical. These could include rankings, public policies, accreditation documents, labour-market reports, student feedback and/or peer-reviewed evidence. Personal data or confidential institutional material needs to be governed separately.

Analysis gives acquired signals the meaning of implications. The analytical task is concerned with comparing the source, assessing its credibility, identifying the patterns in the source, and interpreting the source in relation to the explicit academic decision. Competitive-intelligence maturity models view analysis as a competency that evolves over time, which can be attained through roles, methods, technology and learning (Madureira et al, 2023). From another tradition, analytics studies come to the same conclusion. These large datasets provide a strategic benefit if conceptual differentiation, human understanding and analysis of the information is aligned with an operational question (Ghasemaghahi, 2021; Ranjan & Foropon, 2021). A faculty committee that looks at curriculum evidence in isolation rather than in the context of the disciplines can result in precision without relevance.

The key issues for dissemination are time, audience, format and dialogue. If a report doesn't arrive at the faculty soon after a decision, it becomes of limited value. If the assumptions of a report are not subject to questioning, then it is of limited value. Competitive insight research indicates that insights gained by professionals need to be extracted and presented in a manner that decision makers can understand (Qian et al., 2024). In universities, dissemination is more than a managerial shout. The faculty is a source of analysis and expertise. Dissemination should then provide opportunities to look at evidence, question interpretations and spell out uncertainty.

Intelligence turns into action at utilization. It covers curriculum redesign, teaching priorities, decisions made by faculty, allocation of resources, and follow-through. According to Olszak et al. (2023), competitive intelligence can be a lever of added value, but it is highly dependent on its use. The study conducted by Bao (2020) in China also correlates competitive intelligence to innovation, and care must be taken when making generalizations from sector to university. Since institutions can



gather and disseminate information without altering a decision, utilization should be documented. While not a separate construct in the current workbook, feedback closes the circle when implemented.

The four dimensions are considered as first-order capabilities each. They are not replaceable. There are two ways of scanning broadly and analysing, which are less broad. May be able to deliver strong analysis but in a selective manner. May be able to communicate evidence but not authority or resources of use, or accountability for use. A competitive-intelligence maturity is thus based on balanced development and not on a single high score. This logic also applies to the analysis of overall scores as well as dimension scores.

Taken together, the literature suggests that competitive intelligence should not be equated with the volume of data available to an institution. Analytics research emphasizes technical and analytical capability, whereas competitive-intelligence research places greater weight on decision relevance, interpretation, dissemination, and use (Ghasemaghaei, 2021; Madureira et al., 2023; Ranjan & Foropon, 2021). The distinction is important in universities because decision authority and expertise are distributed across professional groups. A technically strong dashboard can therefore coexist with weak intelligence capability when faculty cannot question its assumptions, contribute disciplinary interpretation, or connect the analysis to a defined academic decision. The present framework adopts this organizational view of intelligence rather than treating information systems as a substitute for intelligence.

2.2 Transformational leadership as an information-conversion practice

Transformational leadership is well known by the four characteristics of idealized influence, inspirational motivation, intellectual stimulation, individualized consideration. The evidence from the contemporary reviews is associated with the leadership pattern and performance in organizational settings, and also observes variability in context, measurement, and mechanisms (Agazu et al., 2025). Currently, the four dimensions are not considered as personality dimensions in the present framework. It reads them as practices as perceived by the faculty which could be reinforced or undermined by the institutional information.

Credibility – the prerequisite for idealized influence. When decision-making is open, there is a clear account of what's happened, and it's clear that there are stated academic values which are visible when things go wrong, faculty are more likely to see principals as principled. Credibility is not enough from intelligence. The leadership team must demonstrate how sources have been selected, how conflicts between the different signals have been dealt with and why some evidence is more important than others. Dissemination is thus a key issue. It allows faculty to determine if leaders model the standards they ask of others.

The inspiration is based on direction that is ambitious and feasible. Without environmental understanding, vision can turn into a Whisper. Competitive intelligence can reinforce a vision through the relationship with the changes in student needs, disciplinary practice, technology, regulation and employment. The relevance of analysis is particularly important because a leader needs to make sense of the external signals and make a coherent narrative of what the institution should defend,



prevent, initiate, or build. The outcome isn't just a more enlightened vision. It has a higher likelihood of being examined.

The leadership dimension which has the closest relationship to analysis is intellectual stimulation. It involves challenging assumptions, thinking out of the box, and encouraging experimentation. This dimension would be in conflict with any kind of intelligence process in which the analytical outputs are accepted as a fact. A process on the other hand that does not bring the uncertainty, compares alternatives, and invites disciplinary interpretation can provide a legitimate basis for challenge. According to Sandoval-Ríos et al. (2025), data literacy plays a pivotal role in making evidence-informed teaching decisions. Academic leadership is no exception: faculty must have the ability and authority to question intelligence, rather than merely take it in.

Individually considering means attentiveness to various professions and career phases. This dimension can be supported by competitive intelligence when developing capability gaps are identified as different or when leaders use evidence to customize capability building opportunities in line with institutional analysis. But personalization can also be intrusive when data are used for labelling faculty or for automated decisions. The leadership in this must therefore maintain explanatory, proportional and the challenge to interpretation. It is better to support, not expand surveillance, but that's what the practical benefit of intelligence is.

One more boundary provided by job demands–resources theory. Academic change can also provide resources, such as clarity and support, but also generate workload and uncertainty (Bakker et al., 2023). A faculty member might struggle to get to grips with change, and poorly managed intelligence systems could put an added strain on faculty through constant monitoring and initiative overload. The framework therefore requires positive correlations, but not necessarily the more the better when it comes to intelligence activity. Quality, participation and use are more important than volume.

The two theoretical traditions therefore explain different parts of the same organizational problem. Transformational-leadership research begins with leader behaviour and usually traces its consequences for attitudes or performance, while competitive-intelligence research begins with information and follows its conversion into action. Neither perspective, on its own, specifies how evidence becomes a credible leadership practice. This framework joins the two by treating the quality of acquisition, interpretation, dissemination, and use as part of the informational setting in which transformational leadership is experienced. The argument is relational, not causal, and requires field testing.

2.3 Higher education, faculty participation, and intelligence governance

The universities differ from firms in terms of mission, authority, professional autonomy and plurality of stakeholders. The term competitive must be taken in the proper context. Institutions can compete for students and staff, for funding, for partnerships, and for reputation; but they can also work together and be responsible for common public tasks. In this research, competitive intelligence is a disciplined knowledge of the environment and an analysis of competition. It is not about students or faculty as objects of the market, nor about hidden collecting.

The importance of intelligence practices is evident in higher education applications. Oraee (2023) defines information behaviour in the context of competitive intelligence process in medical-sciences universities. This article, by Mgweba et al. (2024), discusses competitive intelligence from a student recruitment perspective in public universities. These studies focus on the information needs, collection and strategic use of information within educational organizations. The current article carries this thinking further than recruiting only – towards undergraduate instruction and faculty understandings of leadership.

With digital transformation, there is an increased demand for governance. According to Benavides et al. (2020), there are three pillars of higher-education transformation: strategy, people, and processes, and technology. Kang and Xu (2025) present the development of research on the digital transformation of Chinese Higher Education. The result of these changes is that there are more signals for academic leaders to read. They also raise the prospect of short-lived initiatives, fragmented dashboards and decisions based upon data that is gathered but not for a specific question.

The proposed model's governance mechanism is through faculty participation. Faculty have some unique knowledge of their discipline, teaching experience and local knowledge that are not adequately captured in the central system. Dissemination should be bi-directional. Leaders share evidence, faculty analyze and interpret, and faculty report on implications for practice. This configuration mirrors the concept of knowledge integration in analytics capability studies which highlights the value that can be created by synthesizing technological resources with human and organizational capabilities (Ciampi et al., 2021; Mikalef et al., 2020).

The field test will need to be culturally and institutionally adapted for the China context. The norms, rules, and routines of faculty collective decision-making, as well as administrative structures, can influence faculty perceptions of leadership and information sharing. Translation should be performed using forward translation, back-translation, expert and cognitive review. Regions, university types, ranks, and disciplines should only be compared after testing for measurement invariance. If those steps were not taken, numeric group differences might be due to interpretation of items rather than substantive differences.

2.4 Sustainable competitive intelligence, governance, asymmetry, and feedback

A university's competitive advantage is not limited to being the “best” in the market or having a short-term ranking. It is more accurately viewed as a sustainable institutional ability to identify relevant change, to sustain organizational learning, to meet the needs of its stakeholders, and to make use of credible intelligence to inform educational decisions that are sustainable. When the signals captured from the environment are interpreted, shared, acted upon, and learned by the organization, competitive intelligence adds to this capability (Awamleh & Ertugan, 2021; Mikalef et al., 2020). Intelligence is thus sustainable if it enables adaptation and learning; information alone is not enough.

The control architecture for that process is intelligence governance. It establishes the purpose for which information is gathered, the sources of acceptable information, who can be relied upon to analyze information and who can use the outputs of analysis, how uncertainty will be communicated,



and who will be held responsible for decisions based on the intelligence. In universities these questions are particularly significant because strategic information is spread throughout central administration, faculties, departments and programme committees, the student-support facilities, and individual academics. Governance, thus, needs to be both traceable and accountable, but also respect privacy, professional autonomy and the ability to question interpretations.

There is a related problem, called information asymmetry. Senior administrators might be in possession of policy, benchmarking, financial, or institutional information that is not easily accessible to faculty, and faculty may have disciplinary and classroom information that isn't easily available to central decision makers. When dissemination is two-way, rather than one-way, competitive intelligence can decrease this asymmetry. Strategic and local knowledge can be brought into the same decision-making process through shared evidence, source documentation, and opportunities for interpretation. In contrast, a highly centralized intelligence can exacerbate asymmetry, if the results are disseminated without their pre-understanding, short of them, or without their evidence.

Feedback should therefore always be regarded as an ongoing component in the competitive-intelligence cycle. If intelligence is used to inform a curriculum, teaching, staffing or faculty-development decision, implementation should be evaluated against a predetermined criterion. The resulting evidence is used as a new input for acquisition and analysis, thus providing a cycle of acquisition, analysis, dissemination, utilization, feedback, and re-scanning (Cavallo et al., 2021; Madureira et al., 2023). Feedback is not currently a separate construct in the item bank, and is therefore not measured here, but is kept here as a governance requirement which needs to be operationalised in future field testing.

There are also differences in the use of intelligence at an institutional level. University-level intelligence can be used for long-term positioning, policy response, resource priorities and partnerships. Disciplinary investment and programme portfolios can be informed by faculty or school-level intelligence. It can be utilized by departments and programme committees in curriculum design, assessment, support for students, and employer alignment. Selected intelligence can be used as a basis for adapting teaching at the individual faculty level, for professional development. Sustainable competitive intelligence is thus based not only on the production of intelligence, but also on the match of form, timing, decision rights and feedback mechanisms of the intelligence to the level at which the decision is made.

2.5 Research gap and originality

The theoretical novelty comes from considering the conceptualization of transformational leadership as not entirely independent of, but partially reliant on, a system to transform intelligence. Traditional competitive-intelligence studies typically come to a conclusion in one of three ways: Innovation, Agility and/or Performance. The leadership research that already exists typically starts with leader behaviour and then proceeds to attitudes or outcomes. The framework bridges the gap between the environment and faculty perceptions of leadership with an organizational process. It asks if the leadership seems more transformational when the institution gets and can credibly analyze relevant signals, shares them openly and transparently, and takes them wisely and responsibly.

A novelty of the proposed field design is the simultaneous assessment of four intelligence and four leadership factors. This avoids redefining general digital literacy as competitive intelligence and prevents leadership from being reduced to a single global item. The methodological contribution lies in testing whether the proposed scoring and analytical sequence can recover the designed construct structure without treating those numerical patterns as field evidence. Within that boundary, the demonstration evaluates internal consistency, convergent and discriminant diagnostics, clustered inference, fixed effects, robust estimators, leave-one-institution-out checks, and institution-grouped prediction. This alignment between constructs, analytical procedures, evidence, and claims follows contemporary methodological recommendations rather than relying on a single significance test (Aguinis et al., 2020).

The current workbook does not address the issue of the data gap. No real archive of the respondent has been provided. The article thus considers the numerical analysis as an illustration of the design and not as evidence from the fields. This distinction is a part of the contribution and generated records can also identify coding mistakes, poor scoring rules, collinearity, and/or an inconsistent analysis plan prior to the recruitment of the participants. They are unable to determine prevalence, effect size, difference among subgroups, or impact of policy.

The practical originality is an intelligence to leadership audit. Academic leaders can review the "bottlenecks" in the cycle. Weak acquisition indicates blind spots. Weak analysis indicates that the interpretive capacity is lacking. If dissemination is weak, there is a hint of exclusion or delay. There is weak utilization which indicates that evidence is not linked to authority and follow-through. The four dimensions of leadership then demonstrate how these failings are felt among faculty. The audit is not a ranker.

2.6 Hypotheses

The integrated framework leads to five directional hypotheses for the designed analysis. Each hypothesis concerns association. None is stated as a causal effect.

- H1. Competitive-intelligence acquisition is positively associated with overall transformational leadership among faculty who teach undergraduate programmes.
- H2. Competitive-intelligence analysis is positively associated with overall transformational leadership among faculty who teach undergraduate programmes.
- H3. Competitive-intelligence dissemination is positively associated with overall transformational leadership among faculty who teach undergraduate programmes.
- H4. Competitive-intelligence utilization is positively associated with overall transformational leadership among faculty who teach undergraduate programmes.
- H5. Overall competitive-intelligence capability is positively associated with overall transformational leadership after faculty and institutional characteristics are considered.

The joint dimension model is especially important. A positive bivariate association can reflect the shared core of the intelligence cycle. Joint coefficients ask whether a dimension contributes distinct information after the other stages are held constant. A weak joint coefficient does not imply



that the stage is unimportant. It may indicate that its variance is shared with acquisition, analysis, or dissemination, or that the generated structure assigns it a smaller direct link.

3. METHOD

3.1 Design and evidence boundary

The present study is a cross-sectional, quantitative and methodological demonstration study that uses a simulation approach. The unit is a simulated profile of a faculty member teaching undergraduate programmes. To test coding/ clustering, the geographic fields are labelled with Chinese province, region, and university type. University codes are generic codes. They are not specific to identify real institutions. No faculty member was recruited, no survey was sent out and no institution provided responses.

This evidence boundary determined the analytic language. The results are presented as associations retrieved from a designed system. The analysis is not representative of the nation and/ or not representative of institutional performance nor does it make a causal claim. It also does not rely upon a generated sample size to demonstrate statistical power for a future field study. The number of universities is a constraint that must be considered in planning field power given the intended multilevel design, the intraclass correlation to be expected, the reliability of the measurements, the smallest effect of interest, and the number of universities to be expected.

Accordingly, the numerical analyses cannot support substantive scientific conclusions about Chinese faculty or universities, and the organizational implications in this article are treated as propositions for field testing rather than evidence-based recommendations. A substantive empirical test requires data collected from real faculty under an approved sampling, consent, and instrument-validation protocol.

Accordingly, the numerical analysis in this manuscript is a methodological demonstration rather than empirical evidence about Chinese faculty or universities. Any claim about prevalence, institutional differences, leadership conditions, or practical impact requires a separate field phase using real faculty responses. That phase should include ethics review where required, documented recruitment and consent, cultural and linguistic validation of the instrument, and a multi-university sampling design. The present analysis cannot substitute for that evidence and no substantive population inference is made from the generated records.

The workbook was reviewed prior to the model specification. The sequence of validation is presented in Figure 2. This series started with identifiers, missingness, ranges of responses, as well as formula checks. It then progressed to measuring diagnostics, explanatory models, robustness testing and predictive validation. This order will minimize the chance of choosing an estimator without verifying the nature of variables.

3.2 Dataset structure and validation

There was a total of 520 rows and 54 columns in the workbook in the analysis sheet. Identifiers of the respondents were distinct. There were 24 anonymized university codes and 12 provincial/municipal labels. The rows spanned four types of institutions, eight disciplinary areas, three academic ranks, four management role categories and some demographic controls. All 32 items were scored on a 7-point scale, ranging from 1 (strongly disagree) to 7 (strongly agree). There were no reverse scored items.

The missing cells in the analysis range were not identified during the audit. The range of responses to all items was within the stated limits of one to seven. The four-item blocks of the composite scores were recomputed and agreed with the items on the workbook. The mean score for acquisition, analysis, dissemination, and utilization was the overall competitive-intelligence score. Overall transformational-leadership score was the average of idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration.

There are no missing data in the table as this is a design generated, and is not expected during fieldwork. Invitations, consent, partial completion, exclusions and pattern of missingness by item and institution should be reported in a real study. However, if the missing-data mechanism and measurement structure are studied, multiple imputation or full-information methods should be considered. Listwise deletion should not be used as a default, as it is easy to do, unless it is the ideal choice for the specific problem at hand.

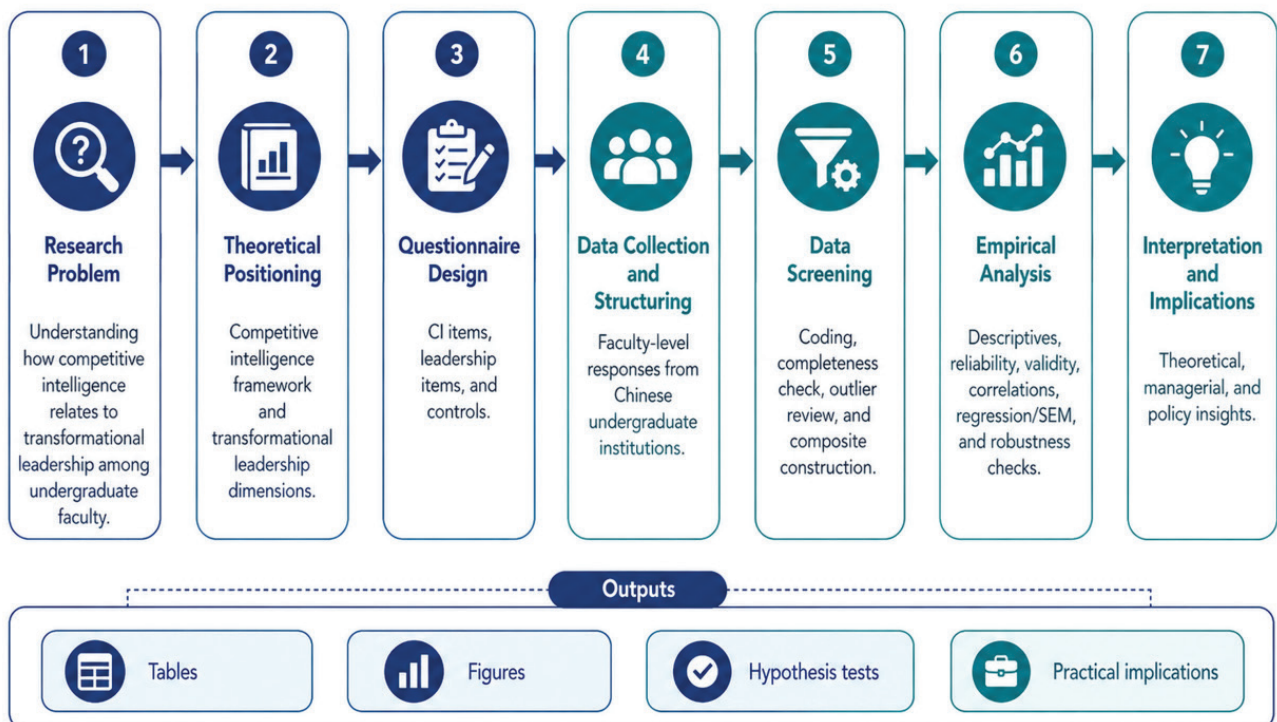


Figure 2. Auditable research workflow and data-processing pipeline. Source: Authors' design.



3.3 Variables and measurement

Table 1 defines the study variables. Competitive-intelligence acquisition involved monitoring policy, teaching technologies, student and employer needs, graduate skills, and similar universities. Analysis included interpretation, benchmarking, credibility assessment and utilization of faculty expertise. Dissemination involved timely sharing across departments, access to evidence, and discussion beyond senior management. Utilization included curriculum use, conversion to priorities for teaching, faculty development decisions, and follow-through.

Four dimensions were used to represent transformational leadership. Ethical consistency, trust, long-term educational interests, and respect for difficult choices were identified as idealized influences. Inspirational motivation included direction, link between faculty and institutional objectives, confidence and enthusiasm. Intellectual stimulation included challenging assumptions, experimentation, multiple perspectives and reasoned disagreement. Individualized consideration included development needs, support for teaching challenges, career stage opportunities, and listening.

An item bank was developed for the framework. It does not appear to be a licensed or previously validated scale. The results of internal consistency and one-factor diagnostics in this article only demonstrate the behavior of the designed items within the records generated. Do not demonstrate content validity, criterion validity, cultural validity or measurement invariance. Prior to administration, a field study needs to seek expert judgment from scholars in competitive intelligence, leaders in higher education, faculty representatives, and psychometric experts.

For comparability, Cronbach's alpha was reported, but not considered as a definitive criterion. When tau-equivalence is not plausible, methodological work indicates that alpha may be misleading, and suggests using reliability estimates based on omega or models (Flora, 2020; Hayes & Coutts, 2020). The one-factor model was used to estimate standardized loadings and composite reliability and average variance extracted since the workbook had four indicators per construct. Typically, the measurement guidance from contemporary literature (Hair et al., 2020) was used to assess the distinction of the constructs in a pairwise manner using the HTMT ratios.

Table 1. Variable definitions and operationalization

Variable	Code	Indicators	Operationalization	Analytical role
CI acquisition	CIA	CIA1–CIA4	Mean of four seven-point items on policy, technology, stakeholder needs, and peer-institution monitoring	Predictor dimension
CI analysis	CAN	CAN1–CAN4	Mean of four items on implication analysis, benchmarking, source credibility, and faculty interpretation	Predictor dimension
CI dissemination	CID	CID1–CID4	Mean of four items on timeliness, cross-unit communication, evidence access, and open discussion	Predictor dimension
CI utilization	CIU	CIU1–CIU4	Mean of four items on curriculum use, teaching priorities, faculty development, and follow-through	Predictor dimension
Overall competitive intelligence	CI	CIA, CAN, CID, CIU	Mean of the four competitive-intelligence dimension scores	Primary predictor



Variable	Code	Indicators	Operationalization	Analytical role
Idealized influence	II	II1–II4	Mean of ethical consistency, trust, long-term educational interest, and respect items	Leadership outcome
Inspirational motivation	IM	IM1–IM4	Mean of direction, goal connection, confidence, and enthusiasm items	Leadership outcome
Intellectual stimulation	IS	IS1–IS4	Mean of questioning, experimentation, multiple perspectives, and disagreement items	Leadership outcome
Individualized consideration	IC	IC1–IC4	Mean of development needs, teaching support, career-stage opportunity, and listening items	Leadership outcome
Overall transformational leadership	TL	II, IM, IS, IC	Mean of the four transformational-leadership dimension scores	Primary outcome
Controls	—	Faculty and institution fields	Teaching experience plus gender, age, rank, degree, management role, university type, discipline, and region	Covariates

Note. CI = competitive intelligence; TL = transformational leadership. All construct indicators use a seven-point agreement scale. The item bank requires field validation before substantive use.

3.4 Statistical analysis

For each dimension and overall score, descriptive statistics (mean, standard deviation, range, skewness, excess kurtosis) were obtained. The designed linear relationships were described using Pearson correlations. A first unrotated principal component was reported as a limited common-method diagnostic over the 32 items. A percentage of less than 50 does not imply that method bias is not present. Stronger field designs should ensure that measurement occasions, sources and formats are separated and statistical checks should be considered as evidence of sensitivity (Jordan & Troth, 2020; Kock et al., 2021).

The major explanatory model was the standardized overall transformational leadership regressed onto the standardized overall competitive intelligence. The controls consisted of categorical variables of gender, age group, academic rank, highest degree, management position, type of university, discipline and region, as well as teaching experience. The 24 university codes were used as clusters for the calculation of the standard errors. This coefficient thus reflects the teeth-grindingly adjusted association for a one-standard-deviation change in competitive intelligence in the specified sample.

A second model was introduced to the four competitive-intelligence dimensions together. Collinearity was explored using variance-inflation factors. Four other models employed an idealized influence, inspirational motivation, intellectual stimulation and individualized consideration as distinct outcomes. The intelligence dimensions were tested in these models for different patterns of relationships with leadership behaviours, instead of the uniform or assumed relationship.

Robustness checks involved changing the estimator or changing the institutional adjustment without changing the focal construct. They involved HC3 standard errors, clustered inference with fixed effects at university level, Huber M-estimation, median regression, a cluster 2,000-resample bootstrap, and leave-one-university-out estimation. The stability determination was based on direction, size and interval overlap of the coefficients. Repeated statistical significance was not considered to be a measure of robustness.

The analytical framework is depicted in Figure 3. The measurement layer deals with the issue of coherence in the behavior of the items being measured. Structural Layer: deals with modified association. The predictive layer asks if the same variables have out-of-group prediction. Agreement within these layers does not imply causal identification, rather it increases the internal demonstration.

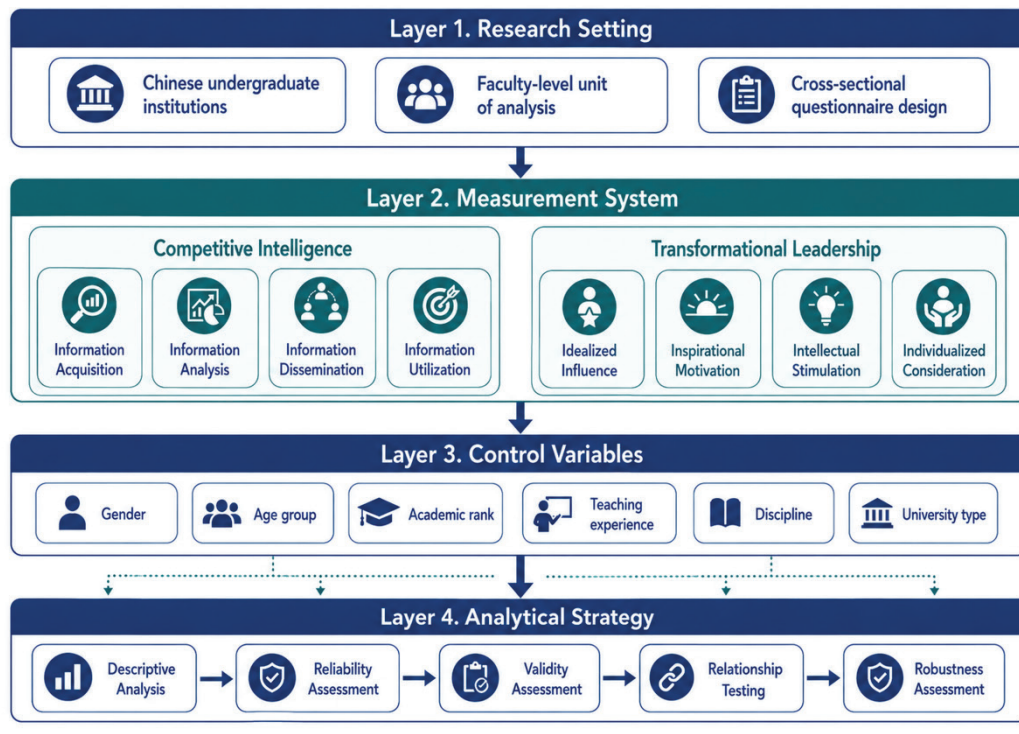


Figure 3. Methodological and analytical framework separating measurement, explanatory inference, and predictive sensitivity. Source: Authors' design.

3.5 Predictive sensitivity analysis

Only a sensitivity analysis was performed using machine learning. As a whole result was transformational leadership. The four competitive-intelligence dimensions, teaching experience and the categorical controls were the predictors. Leadership items were not used as predictor items. Groups were defined in the university codes so that the rows from each code would not be in both the training and the test set. This step mitigates the risk of leakage from the institutions in predictive research (Kapoor & Narayanan, 2023).

The grouped split resulted in 401 cases in 18 university codes being assigned to training and 119 cases in 6 university codes being assigned to testing. Five-fold cross-validation was used to optimize Ridge regression, Elastic Net, random forest and gradient boosting. Cross-validated root mean squared error was used to select models. The measures of final performance were reported as R-squared, RMSE and MAE for the untouched test groups. The best model was obtained on the held-out groups, and permutation importance was calculated.



Practical deployment was claimed without the use of prediction. The test groups were chosen from the same process of generation as the training groups, and the sample is not representative of actual institutional change. A field predictive study should include the reservation of universities from diverse regions and collection waves, calibration, subgroup error analysis, and a comparison of the implications of inaccurate high and inaccurate low leadership predictions. Leadership scores are not to be used automatically for personnel decisions.

4. RESULTS AND DISCUSSION

4.1 Structural audit and descriptive results

The audit retained all 520 generated profiles. The identifier field contained 520 unique values. No missing response was found, and all construct items remained within the one-to-seven scale. The 24 generic university codes were distributed across 12 province or municipality labels. These results confirm structural completeness, not field-data quality.

Table 2 reports descriptive statistics. Competitive-intelligence dimension means ranged from 4.377 for acquisition to 4.490 for dissemination. The overall competitive-intelligence mean was 4.445 (SD = 1.071). Transformational-leadership dimension means ranged from 4.428 for intellectual stimulation and individualized consideration to 4.497 for idealized influence. The overall leadership mean was 4.451 (SD = 1.067). Skewness was modest and negative for every construct, while excess kurtosis ranged from -0.671 to -0.348. The distributions therefore contained no severe univariate distortion within the designed records.

The closeness of the means should not be interpreted as evidence that Chinese faculty perceive all practices similarly. The scores reflect the generation process. Their purpose is to test whether composite formulas and models behave as intended. In a field survey, item distributions may show ceiling effects, acquiescence, or institutional clustering that require ordinal estimators or robust latent-variable methods.

Table 2. Descriptive statistics for competitive-intelligence and transformational-leadership constructs

Construct	Mean	SD	Min	Max	Skewness	Excess kurtosis
CI acquisition	4.377	1.271	1.000	7.000	-0.105	-0.484
CI analysis	4.476	1.316	1.250	7.000	-0.128	-0.644
CI dissemination	4.490	1.270	1.250	7.000	-0.159	-0.532
CI utilization	4.439	1.292	1.000	7.000	-0.242	-0.480
Overall competitive intelligence	4.445	1.071	1.375	6.938	-0.168	-0.348
Idealized influence	4.497	1.350	1.000	7.000	-0.238	-0.671
Inspirational motivation	4.451	1.297	1.000	7.000	-0.137	-0.466
Intellectual stimulation	4.428	1.298	1.000	7.000	-0.252	-0.425
Individualized consideration	4.428	1.279	1.000	7.000	-0.184	-0.524
Overall transformational leadership	4.451	1.067	1.375	6.938	-0.225	-0.368

Note. N = 520 generated profiles. Descriptive values characterize the designed records and are not population estimates.

4.2 Measurement diagnostics

The measurement diagnostics appear in Table 3. Cronbach's alpha ranged from .830 for acquisition to .871 for analysis. Composite reliability was almost identical, ranging from .830 to .871. Standardized one-factor loadings ranged from .709 to .806. Average variance extracted ranged from .551 to .627, exceeding the conventional .50 reference point for every construct.

HTMT ratios were below .85. The largest value was .728 between acquisition and utilization. Ratios among leadership dimensions ranged from .609 to .666. These values indicate that the generated design preserves distinction among the eight first-order constructs. They do not validate the item bank for faculty populations. The first principal component across all 32 indicators explained 36.0% of variance. This result does not indicate a dominant single factor, but common-source concerns remain because all items share the same response format and occasion.

Correlations are shown in Figure 4 and in Table 3. The four competitive-intelligence dimensions correlated from .569 to .612. The four leadership dimensions correlated from .524 to .573. Cross-block correlations ranged from .281 between utilization and individualized consideration to .418 between analysis and inspirational motivation. The pattern supports related but non-redundant domains within the designed system.

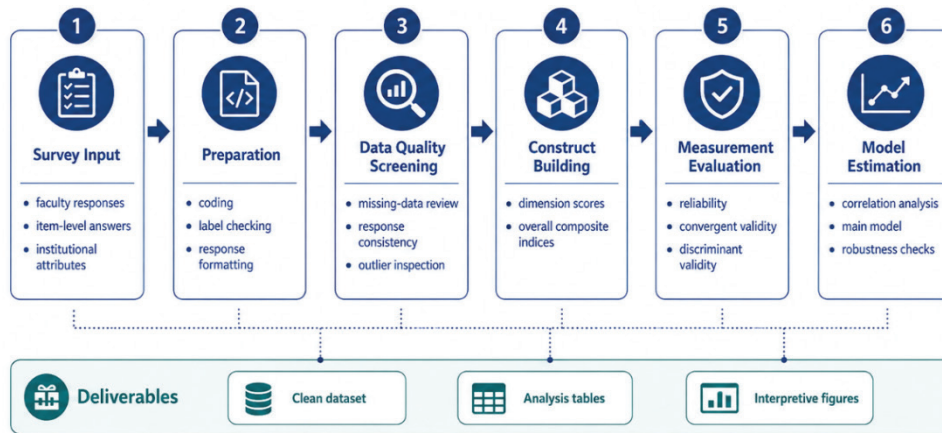
Table 3. Correlation, reliability, and validity diagnostics

Panel A. Reliability and convergent evidence					
Construct	Alpha	CR	AVE	Loading range	Maximum HTMT
CIA	0.830	0.830	0.551	0.709–0.764	0.728
CAN	0.871	0.871	0.627	0.778–0.806	0.702
CID	0.856	0.856	0.598	0.748–0.794	0.702
CIU	0.853	0.853	0.593	0.742–0.794	0.728
II	0.866	0.866	0.617	0.779–0.797	0.666
IM	0.854	0.854	0.595	0.734–0.804	0.666
IS	0.857	0.857	0.599	0.759–0.794	0.663
IC	0.854	0.854	0.595	0.763–0.779	0.666

Panel B. Pearson correlations								
Construct	CIA	CAN	CID	CIU	II	IM	IS	IC
CIA	—							
CAN	0.591	—						
CID	0.578	0.605	—					
CIU	0.612	0.578	0.569	—				
II	0.373	0.367	0.331	0.308	—			
IM	0.366	0.418	0.399	0.351	0.569	—		
IS	0.347	0.336	0.358	0.306	0.524	0.567	—	
IC	0.346	0.359	0.374	0.281	0.573	0.569	0.537	—

Note. Alpha = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; HTMT = heterotrait–monotrait ratio. The first principal component explained 36.0% of item variance.

Figure 4: Data Processing Pipeline



Pipeline for converting structured faculty responses into analysis-ready evidence.

Figure 4. Correlation heatmap for the eight first-order constructs. Source: Authors' analysis.

4.3 Overall and dimension-level associations

Table 4 reports the explanatory models. In the overall model, competitive intelligence was positively associated with transformational leadership after controls ($\beta = .511$, 95% CI [.426, .596], $p < .001$). The model explained 32.9% of variance in the standardized outcome. H5 was supported within the designed analysis.

The joint dimension model explained 33.6% of variance. Acquisition retained a positive coefficient ($\beta = .178$, 95% CI [.054, .302], $p = .005$). Analysis was also positive ($\beta = .182$, 95% CI [.073, .290], $p = .001$). Dissemination had the largest joint coefficient ($\beta = .211$, 95% CI [.088, .334], $p = .001$). Utilization was positive but uncertain ($\beta = .044$, 95% CI [−.066, .154], $p = .432$). Variance-inflation factors ranged from 1.89 to 1.96, so the uncertain utilization coefficient was not explained by severe collinearity. H1–H3 were supported in the joint designed model, whereas H4 was not.

Figure 5 displays the joint coefficients and their confidence intervals. The plot makes two points visible. First, the intervals for acquisition, analysis, and dissemination exclude zero. Second, the interval for utilization is broad relative to its coefficient and crosses zero. The result should not be read as evidence that intelligence use is unimportant. In the designed records, utilization shares substantial variance with earlier stages and carries little additional linear information once those stages are included.

The leadership-dimension models show a differentiated pattern. Idealized influence was associated with acquisition ($\beta = .197$) and analysis ($\beta = .165$), while dissemination was positive but uncertain. Inspirational motivation was associated with analysis ($\beta = .194$) and dissemination ($\beta = .182$). Intellectual stimulation was associated with acquisition ($\beta = .143$) and dissemination ($\beta = .182$), while analysis was borderline ($p = .081$). Individualized consideration was associated with acquisition ($\beta = .144$), analysis ($\beta = .133$), and dissemination ($\beta = .221$). Utilization did not retain an independent coefficient for any leadership dimension.

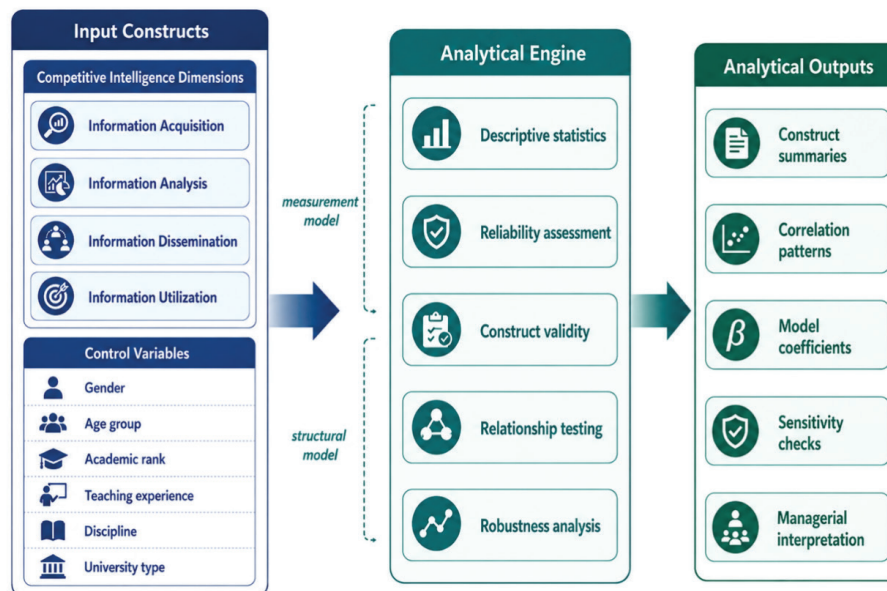
These patterns are consistent with the framework's information-conversion logic. Acquisition supplies the external and stakeholder evidence that can ground credibility and challenge. Analysis supports interpretation and direction. Dissemination creates access, dialogue, and visibility. Utilization occurs later in the cycle and may be experienced indirectly through these practices rather than as a distinct faculty perception. This is an interpretation of the designed structure, not a discovery about real universities.

Table 4. Main model results

Panel A. Overall and joint competitive-intelligence models						
Model	Predictor	β	Clustered SE	95% CI	p	R ²
Overall	Overall CI	0.511	0.043	[0.426, 0.596]	< .001	0.329
Joint	CIA	0.178	0.063	[0.054, 0.302]	0.005	0.336
Joint	CAN	0.182	0.055	[0.073, 0.290]	0.001	0.336
Joint	CID	0.211	0.063	[0.088, 0.334]	< .001	0.336
Joint	CIU	0.044	0.056	[-0.066, 0.154]	0.432	0.336

Panel B. Joint models for leadership dimensions						
Outcome	CIA β	CAN β	CID β	CIU β	R ²	
Idealized influence	0.197*	0.165*	0.108	0.035	0.217	
Inspirational motivation	0.096	0.194*	0.182*	0.074	0.281	
Intellectual stimulation	0.143*	0.102	0.182*	0.048	0.230	
Individualized consideration	0.144*	0.133*	0.221*	-0.014	0.236	

Note. All outcomes and continuous predictors are standardized. Models include faculty and institutional controls. Standard errors are clustered by 24 university codes. * p < .05. CIA = acquisition; CAN = analysis; CID = dissemination; CIU = utilization.



Analytical path from observed variables to interpretable research outputs.

Figure 5. Standardized coefficients and 95% confidence intervals from the joint overall model. Source: Authors' analysis.

4.4 Robustness and sensitivity

Table 5 presents the robustness checks. The focal overall coefficient was .511 with university-clustered standard errors and .511 with HC3 standard errors. Adding university fixed effects produced $\beta = .500$. Huber M-estimation produced $\beta = .517$, and median regression produced $\beta = .549$. A 2,000-resample cluster bootstrap gave a percentile interval of [.419, .593]. The leave-one-university-out coefficient ranged from .491 to .526.

The narrow leave-one-out range indicates that no single generic university code drives the overall association. The fixed-effects estimate shows that the relationship remains when all time-invariant differences between codes are absorbed. The robust and median estimates indicate that the coefficient is not dependent on ordinary least-squares sensitivity to large residuals. Again, these tests establish internal stability under alternative computations. They do not provide external validity.

Table 5. Robustness and predictive sensitivity analysis

Panel A. Overall competitive intelligence coefficient across estimators					
Estimator	β	SE	95% CI	p	Interpretation
Cluster-robust baseline	0.511	0.043	[0.426, 0.596]	< .001	Primary specification
HC3	0.511	0.039	[0.434, 0.588]	< .001	Heteroskedasticity-robust inference
University fixed effects + cluster	0.500	0.046	[0.409, 0.590]	< .001	Absorbs code-level constants
Huber M-estimation	0.517	0.040	[0.440, 0.595]	< .001	Limits residual influence
Median regression	0.549	0.047	[0.457, 0.641]	< .001	Models conditional median

Panel B. Grouped held-out prediction				
Model	CV RMSE	Test R ²	Test RMSE	Test MAE
Ridge	0.915	0.210	0.987	0.805
Elastic Net	0.906	0.233	0.973	0.804
Random Forest	0.904	0.194	0.997	0.821
Gradient Boosting	0.910	0.210	0.987	0.816

Note. Cluster-bootstrap 95% interval = [0.419, 0.593]. Leave-one-university-out coefficient range = 0.491–0.526. Prediction used 18 training and six test university codes.

4.5 Predictive sensitivity

The predictive comparison appears in Figure 6 and Table 5. Elastic Net achieved the strongest held-out performance, with $R^2 = .233$, RMSE = .973, and MAE = .804. Ridge regression produced $R^2 = .210$, random forest .194, and gradient boosting .210. The small performance differences and the advantage of a regularized linear model indicate that the designed relationship is mostly additive and linear.

Predictive performance was moderate. The explanatory model's in-sample R-squared should not be compared directly with withheld-out R-squared because the samples, fitting objectives, and institutional split differ. The decline is expected and is informative. It shows why explanatory fit should not be presented as predictive accuracy.

Figure 7 reports permutation importance for Elastic Net. Analysis produced the largest mean reduction in held-out R-squared when permuted (.072), followed by dissemination (.067) and acquisition (.062). Utilization contributed only .006. Demographic and institutional indicators were much smaller. The importance pattern resembles the joint regression, which strengthens internal coherence. It remains specific to the generated structure and the selected split.

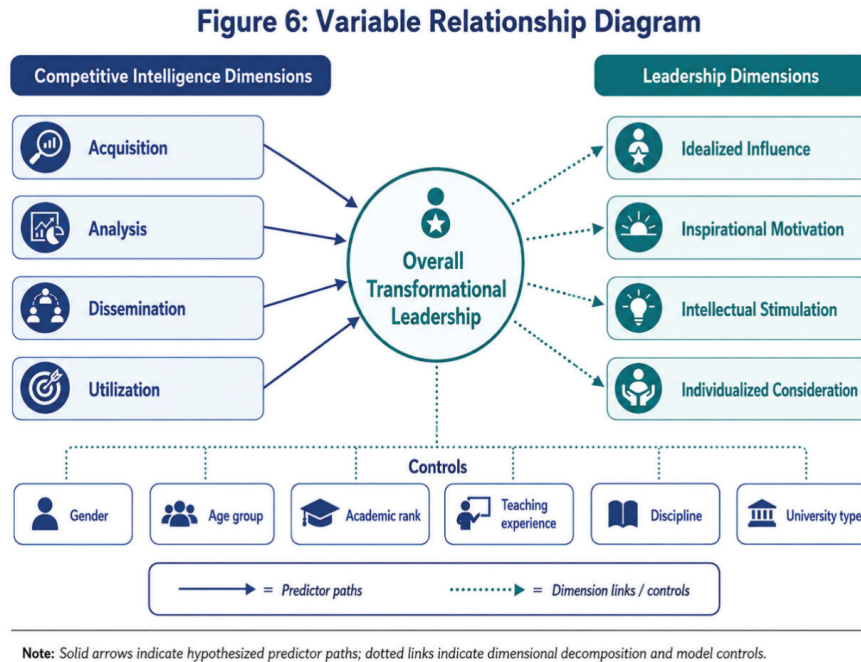


Figure 6. Held-out predictive comparison using an institution-grouped split. Source: Authors' analysis.

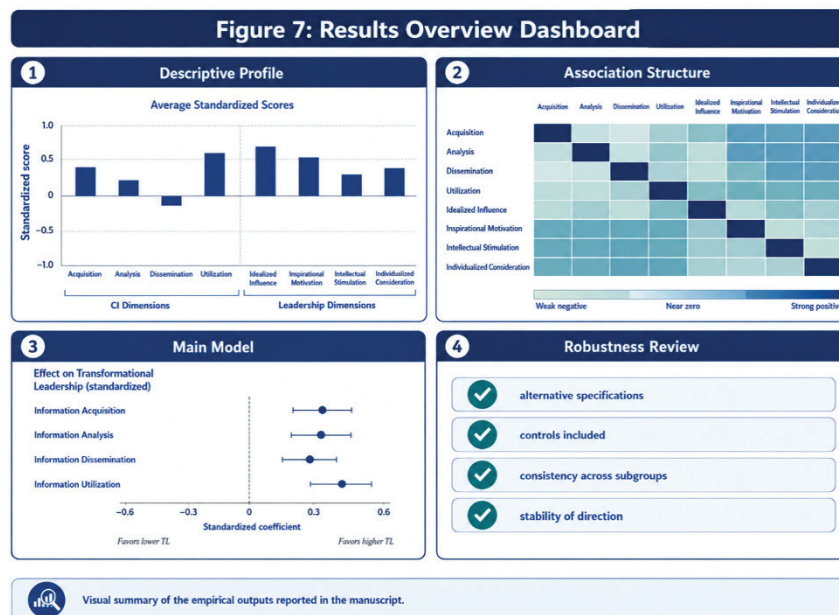


Figure 7. Permutation importance for the best held-out model. Source: Authors' analysis.

4.6 Principal findings

The article questioned whether there was a coherent connection between competitive-intelligence acquisition, analysis, dissemination and utilization and transformational leadership among faculty members teaching undergraduate programmes. There are three findings that make up the answer. First, there was good internal consistency and satisfactory separation in the designed records for the eight-item blocks. Second, there was a stable positive relationship between overall competitive intelligence and overall transformational leadership on a variety of estimators. Third, the joint and predictive models emphasized acquisition, analysis, and dissemination, and only contributed a small amount of independent information for utilization.

The most significant part of the result is not the magnitude of the individual coefficient. It's the way in which the intelligence cycle unfolds. The practices relating to the visibility and interpretability of information were most strongly associated with a transformational approach to leadership. Leaders appear credible when evidence is gathered purposefully. They are more directive when there is a linkage between external change and institutional priorities in the process of analysis. They encourage thinking and identify individual needs during the sharing of information in a manner that will enable faculty to be a part of the process. A measure of utilization can still be relevant, but these may manifest themselves in earlier stages or via outcomes not recorded here.

The utilization result also keeps one from making a too simple conclusion. Intelligence would be the deciding step in a model that focused solely on action. The planned analysis rather indicates that it is not possible to create a clear impression of transformational leadership when the implementation takes place without acquisition quality, analytical credibility, and transparent dissemination. This interpretation is coherent with the research on the competitive intelligence maturity that focuses on the integration of the stages of the process as a whole, rather than on each one individually (Madureira et al., 2023).

The comparison with other higher-education applications of competitive intelligence sharpens this interpretation. Oraee (2023) examines information behaviour within competitive-intelligence processes in medical-sciences universities, while Mgweba et al. (2024) focus on competitive intelligence as a strategic tool for student recruitment in public universities. Those studies place intelligence around information needs and strategic organizational functions. The present framework shifts the point of attention to faculty-facing academic decisions. That difference matters because undergraduate teaching depends on distributed professional expertise. Intelligence that is useful for a centralized strategic function may not support transformational leadership unless faculty can inspect the evidence, contribute interpretation, and see how it enters a decision.

4.7 Theoretical implications for competitive intelligence

Leadership is not just a contextual source or a source of managerial support; it is IN the intelligence cycle. In this context, faculty perceptions of leadership are a result of what occurs with information once it is gathered. Evidence that arrives too late, or is inaccessible or unchallengeable



does not make up for weak technical systems. An institution can thus have sophisticated analytics but not enhance the credibility of its leadership.

The four information stages and the four leadership dimensions are also separated, as these do help to clarify the explanation. Acquisition increases evidence to inform judgement, and thus best fits the criteria for credible influence and intellectual stimulation. Analysis is the foundation of interpretation and direction. There are four dimensions of dissemination, since transformational leadership is experienced through access, communication and dialogue. These are suggestions, rather than one-way causal paths, for longitudinal testing.

Governance is the next implication. Don't assume competitive intelligence equals more monitoring. While open-source intelligence, professional content, and analytics can broaden awareness (Lutz & Bodendorf, 2020; Qian et al., 2024), institutions still need a clear purpose, source standards, access rules, and accountability. Academic freedom and professional judgement set clear boundaries on what should be collected and how it can be used. Deliberation should be guided by intelligence, not replaced.

Reciprocity is also a crucial element. Transformational leadership can strengthen intelligence capability by fostering faculty to report weak signals and question existing assumptions and offer expert interpretations. A credible vision can also narrow the acquisition focus to questions that matter. In future fieldwork, therefore, it would be wise to consider paths that are lagged and reciprocal rather than one-directional.

International higher-education applications of competitive intelligence also reveal a difference in emphasis. Oraee (2023) examines information behaviour within the competitive-intelligence process in medical-sciences universities, while Mgweba et al. (2024) focus on competitive intelligence as a strategic tool for student recruitment in public universities. Those applications show the value of structured intelligence for institutional decisions, but they leave faculty-facing academic leadership less explicit. The present framework therefore extends the discussion from information acquisition for specific strategic functions to the governance, interpretation, dissemination, and feedback processes through which faculty can participate in academic decisions. This comparison also cautions against assuming that intelligence practices developed for centralized strategic functions transfer unchanged to distributed academic settings.

4.8 Implications for leadership research

Research in leadership is given an explicit informational basis. The idealized influence is frequently talked about in terms of ethics, or in a symbolic way. The framework includes a traceability of evidence. Leaders' values can be seen in the way they choose their sources, in the way they deal with awkward findings, and in whether or not they explain their reasons for deciding. This inspirational motivation is provided with a strategic base, since vision is linked to environmental interpretation. Access to evidence and uncertainty provide an infrastructure for intellectual stimulation. Development support is supportive when it is based on proper and meaningful data, and thus has a diagnostic quality.

This is in line with other findings that leadership, engagement, satisfaction, and wellbeing are linked (Abolnasser et al., 2023) but without implying that there is a direct link between them in



the context of Universities. In China, research in universities indicates that there is a connection between work demands, support, digital acceptance and health well-being (Xu et al., 2023; Wei et al., 2025). One way that the intelligence framework can help leaders consider how to structure those conditions is not to have them all—just to determine which signals should be attended to and how faculty should engage in responding.

This is also designed to prevent charismatic overreach. When a confident vision stifles evidence or when a vision is considered a form of disloyalty, it can be detrimental. Evaluating transformational leadership should therefore be done along with intelligence governance. Leaders should be assessed both on the basis of their capacity to inspire change and on the basis of the availability of evidence for the change, the capacity to question it, and the ability to link it to a documented decision pathway.

4.9 Methodological contribution

In terms of methodology, the article maintains transparency of evidence chain. It starts by determining the status of the records, then looks at the workbook, item blocks and makes estimates of adjusted associations, modifies the estimator and tests performance on held-out institutional groups. Every stage addresses a separate question. Reliability is a concern with item coherence. HTMT is related to separation of constructs. Adjusted association is clustered regression. POTW prediction relates to unseen codes.

These questions should not be “lumped together”. No, a high alpha is not a valid indicator of validity. A stable coefficient doesn’t necessarily imply temporal order and good in-sample fit doesn’t necessarily imply prediction. The design is thus aligned with suggestions for matching each claim with the evidence that can support the claim (Aguinis et al., 2020; Hair et al., 2020).

The created design also reveals a restriction that is not apparent in beautiful designs. The data-producing process includes the intended relationships, so it is expected that statistical recovery will be performed. Besides testing code and interpretive discipline, it is useful for testing, not for novelty through significance. The field study can be truly informative only when the relationships can go wrong, the objects can act in unexpected manners, and the institutions can be different in unexpected ways.

4.10 Practical and managerial implications

For academic leaders, the framework provides a blueprint for doing an intelligence audit based on the four questions. What are the signals learned, who determines what they are important, and why? How is the credibility of the source and implications for the institution examined? Who gets the intelligence that is produced, how, and how much opportunity do they have to dispute it? What changed and how was follow-through reviewed? A university without an ability to answer such questions might have information systems without an intelligence capability.

It is important that acquisition is selective and decision-guided. Signals from undergraduate education can come in many forms, such as policy shifts, feedback from students, learning analytics,



expectations from employers, standards, peer institution efforts and new teaching tools. Leaders should start with a known uncertainty. A lack of decisions in broad monitoring can lead to an overload and faculty scepticism.

Analysis should be across functions. While consistency can be achieved with central analytics teams, disciplinary interpretation is key. Faculty should have the ability to review the quality of sources, question benchmarks, and discuss local constraints. By this method, there is less chance of rankings, dashboards, or algorithm recommendations being taken for granted as fact. It also enhances intellectual stimulation by enticing people to disagree as a way of thinking.

Dissemination should be done in a timely, layered and reciprocal manner. Senior leaders require a short decision brief; faculty committees require assumptions, source notes and uncertainty. Communication needs to differentiate between known, inferred and contested. Leaders should also record any changes to the interpretation made as a result of faculty input. Otherwise, consultation is just a symbolic gesture.

If you don't have authority and feedback, it is not possible to utilize. Intelligence should be associated with a named decision, responsible unit, implementation date and a review criterion. In the designed results, it is a warning not to measure the use based on general perceptions, because the weak independent utilization coefficient indicates that. The field instrument should include behavioural indicators of documented decisions, completed actions, post-implementation review and maintaining confidentiality.

The practicum application is for faculty development. Information on teaching technologies or on graduate skills should not be translated directly into standardised training. Leaders should take into account institutional priorities, career stage, discipline, workload, and prior capability. Individualized consideration should be supported in a non-stigmatising and customized way. Faculty should be able to read and challenge the evidence that is used in the recommendation for development.

For institutional intelligence systems, the managerial implication is that a dashboard or analytics platform should not be treated as a complete competitive-intelligence system. A usable system needs a defined decision question, documented source provenance, an identified analytical responsibility, rules for dissemination, a named decision owner, and a scheduled feedback point. These elements create an auditable path from environmental signal to institutional learning. They also make it easier to distinguish an information problem from a governance problem when a decision fails to produce the expected result.

Strategically, the framework suggests different uses at different levels of the university. Senior leadership can use intelligence for long-range priorities and policy response; faculties and schools can use it to review programme portfolios and capability needs; departments can use it for curriculum and assessment decisions; and individual faculty members can use selected evidence to adapt teaching and development. The value of the system depends on whether intelligence reaches the level where action is authorized and whether the consequences of that action return to the intelligence cycle as feedback.

4.11 Policy implications

At policy level, the framework favors governed capability over compulsory platform adoption. National and provincial initiatives can encourage evidence-informed teaching without requiring identical intelligence systems. Minimum expectations could cover purpose definition, source transparency, faculty participation, data minimization, access, retention, explanation, and review. These principles would help institutions use competitive intelligence while preserving academic responsibility.

Policy makers should also avoid turning intelligence scores into league tables. A low acquisition score may reflect a specialized mission rather than weakness. A high utilization score may conceal centralized decision making. Capability assessment should therefore support internal improvement, peer learning, and developmental funding. It should not become a punitive ranking unless measurement invariance, criterion validity, and consequences are established.

China's digital higher-education agenda makes these safeguards timely. Studies of educator technology acceptance and generative-AI adoption show that perceived usefulness, support, performance expectations, and work conditions shape implementation (Xu et al., 2024; Wen & Cai, 2025; Xiang et al., 2025). Competitive intelligence can help policy makers distinguish a meaningful capability gap from resistance produced by workload, uncertainty, or poor governance.

4.12 Limitations and directions for future research

The biggest restriction is the source of each record generated. The numerical patterns are not for Chinese faculty, universities, provinces or regions. The university codes are analysis-based tags. The numbers of samples and category distribution were chosen for the workflow test. There are no inferences regarding prevalence, average leadership or institutional difference.

The second restriction is instrument status. There are 32 items which are specific to the study. Internal consistency and one-factor loadings do not guarantee content coverage or cultural meaning of a system-generated construct. A construct map, expert panel, faculty cognitive interviews and bilingual translation should be conducted as the first step in the field programme. When more than one idea is combined, it should be simplified. A pilot sample is used to help with exploratory work, prior to confirmatory testing.

The third limitation is the common-source and cross-sectional design. If the design changes, faculty perceptions of intelligence and leadership would be obtained from different respondents. Procedural controls should include separation of predictor and outcome blocks, clear confidentiality, varied scale anchors (where appropriate), and neutral wording. In a more robust design, faculty surveys and meeting minutes, intelligence briefs, decision logs and leadership assessment from several sources would be linked together.

Clustering is the fourth restriction. It is enough to run the 24 generated codes to test cluster-aware code without ensuring stable field inference. The true study should be conducted at a larger number of universities, and a description of the selection frame should be recorded, as well as plans for unequal cluster sizes. Data should be analyzed with multilevel confirmatory factor analysis, if



available, to distinguish the within- and between-university structure of the data. A small number of clusters should not be used to infer university-level predictors.

The fifth restriction is the time order. Leadership perceptions can be influenced by competitive intelligence, leadership routines can be influenced by competitive intelligence, or both can be influenced by a third factor, like institutional change capacity. A three-wave design would be a more robust test. It might be measured first, perceptions of leadership second, and documented decisions/teaching outcomes third. A cross-lagged or multilevel structural model might then be used to compare directions in the model without making strong causal claims.

The sixth restriction deals with the prediction. The list of universities with the “held out” was created in the same fashion. Geographic and temporal transportability of the results should be tested in future work, as will error across rank, gender, discipline, and university type. Machine-learning models ought to be used for research diagnosis, not for an automatic assessment of leaders and faculty.

There are 5 possible stages that a credible field-validation programme can be carried out in. Stage one is used to define the intelligence construct and ethics rules. Stage two includes cognitive interviews, expert review and translation. Stage three (Q) involves testing the questionnaire and estimating the measurement model. A multi-university, multi-source, preferably longitudinal sample is collected in stage 4. Stage five relates intelligence routines to documented decisions and teaching outcomes. The framework should be used for institutional benchmarking and/or policy evaluation at a later point in time.

Future research should also compare the framework across institutional and national settings rather than assuming that the same governance arrangements apply everywhere. Longitudinal field studies should test whether feedback improves subsequent acquisition and analysis, whether reciprocal dissemination reduces information asymmetry, and whether intelligence operates differently at university, faculty, department, and individual levels. Comparative designs would make it possible to separate general features of competitive intelligence from practices that are specific to a particular governance system.

5. FINAL CONSIDERATIONS

The competitive intelligence framework in this article is used to analyze the transformational leadership of the faculty in the field of undergraduate programs. The framework recognizes that acquisition, analysis, dissemination and utilization are coherent and interconnected aspects of intelligence. It links them to the idealized influence, inspiring motivation, intellectual stimulation and individualized consideration. The core idea is that leadership is manifested in part by how institutions process information into collective judgement and accountable action.

Measurement blocks were consistent and clearly identifiable within the created records. The overall competitive intelligence was positively correlated with overall transformational leadership. The coefficients for acquisition, analysis and dissemination were all positive, suggesting positive relationships with use, which was not supported by independent information. The association of the focal remained unchanged when clustered by fixed effects, by robust estimators, with bootstrap



resampling, and in leave-one-institution-out analyses. The institution-grouped prediction was moderate, with the regularized linear model being the best.

The point of the substantive lesson is not that Chinese universities have a certain leadership profile. There is no evidence to substantiate that. The lesson learned is that the suggested variables, scoring method, and analysis can be tied together for a cohesive field-test design. A real study that is ethically approved, culturally adapted and conducted by multiple universities is the next step. The framework should be used to develop instruments, to govern intelligence and to plan research, but not to make population conclusions, until evidence exists.

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