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Original Article

Leveraging Applied Machine Learning to Uncover Key Drivers of Engagement and Institutional Trust in Higher Education Ecosystems

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Abstract *- This research formulates a predictive framework to examine the determinants affecting staff engagement and institutional trust in higher education by amalgamating organizational psychology with Explainable Machine Learning(XAI). The sample consisted of 70 academic and administrative personnel from the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University, chosen via proportionate stratified sampling. A validated questionnaire (Cronbach's α = 0.95) was employed to assess organizational and motivational factors, as well as engagement and trust. The analysis integrated descriptive and inferential statistics with supervised learning algorithms, such as Logistic Regression, Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Decision Tree, and Naïve Bayes. We used cross-validation and standard metrics like accuracy, precision, recall, and F1-score to measure how well the model worked. The results indicated that organizational factors, including leadership support, communication efficacy, and career advancement opportunities, substantially influenced engagement. Intrinsic motivation—comprising autonomy, recognition, and professional development—exerted a more significant influence on institutional trust than extrinsic factors, such as salary or workload. A comparative analysis revealed that Logistic Regression, SVM, and k-NN surpassed other models in predictive accuracy and F1-score. The framework offers a reproducible and ethically robust methodology for HR analytics in higher education, achieving a balance among model efficacy, interpretability, and equity. This helps to meet the Sustainable Development Goals, especially SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth). It shows how important responsible AI is for creating sustainable academic ecosystems.*

Keywords *- Applied Machine Learning, Organizational Credibility, Educational Data Mining, Trust Modeling, Organizational Trustworthiness, Personnel Engagement.*

1. Introduction

In the fast-changing world of higher education, old ways of managing people, like reward systems that only focus on pay, don't work anymore. Contemporary research underscores that intrinsic factors, such as engagement and institutional trust, significantly impact retention, morale, and the intellectual vitality of academic communities. The global progress in the application of Machine Learning (ML) and Generative Artificial Intelligence (GenAI) provides powerful instruments for understanding and enhancing these psychological and organizational dimensions. A thorough examination covering the years 2018 to 2025 reveals that Machine Learning (ML) is the dominant approach in higher education learning analytics, tackling challenges like predicting student engagement, modeling dropout risk, and forecasting performance. At the same time, GenAI, especially transformer-based models like GPT-4 and BERT, is becoming more popular for tasks like sentiment analysis and personalized feedback. However, there are still not many real-world examples of how to use it and problems with transparency [1]. The use of Artificial Intelligence (AI) and Machine Learning (ML) in schools is showing more and more that they can change things. AI-driven analytics make it easier to create personalized interventions to get students more involved by showing how they behave and allowing for early support. However, they also raise valid concerns about bias, privacy, and fairness [2, 3]. An expanding group stresses the need for Responsible AI frameworks to make sure that learning analytics are open, accountable, and fair for everyone [4]. Extensive examinations of educational data mining and learning analytics confirm that these technologies continue to lead in data-driven decision-making within education, thereby facilitating opportunities for institutional and academic analytics [5]. In the realm of higher education in Thailand, entities like the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University face unique challenges. These organizations are in charge of promoting academic excellence and finding their way in a competitive global market, all while building internal cultures based on trust and long-term engagement. Empirical research conducted in Thailand demonstrates that innovative human resource management practices—including training and development, performance appraisal, and compensation—significantly enhance the sustainable development of institutions [6]. Additionally, effective human resource management positively impacts educational administration in Bangkok's Thai private universities, including pedagogy, research, service, and cultural preservation [7].

Research on university lecturers in Thailand reveals that factors such as workload, burnout, and work–family conflict significantly influence job satisfaction. This indicates that engagement levels and institutional trust in academia are influenced by psychosocial factors [8]. Simultaneous research in Thai state enterprises highlights that organizational attitude, supervisory behavior, career opportunities, employee welfare, and the work environment collectively influence employee engagement, as measured by eNPS [9]. Sectoral insights worldwide suggest that aligning an innovative organizational culture with Human Resource Management fosters innovation; in Thai small and medium enterprises, Human Resource Management and personnel skills act as intermediaries in the relationship between culture and innovation [10]. Artificial Intelligence is also being used by colleges and universities all over the world to change how they teach, run their schools, lead their strategic planning, and help students. This shows how AI can be used in many ways in higher education [11]. Complementary studies underscore the pressing necessity to reassess educational governance in Thai Higher Education Institutions confronted with financial limitations, enrollment difficulties, and globalization pressures [12].

Despite this substantial background, significant research gaps persist, as limited models integrate psychological theories, including self-determination theory, machine learning-driven predictive analytics, and ethical transparency to examine institutional engagement and trust within Thai higher education institutions. Additionally, the research lacks a framework that integrates interpretability with predictive accuracy, which is appropriate for a local institution like Bangkok Thonburi University. This study seeks to fill that void by amalgamating survey-based statistical modeling with explicable machine learning methodologies rooted in Self-Determination Theory (SDT) and the ethical frameworks of artificial intelligence. The goal is to find out what factors are most important for staff at Bangkokthonburi University to be engaged and to trust the institution.

This research enhances academic comprehension by offering a replicable and ethically grounded human resources analytics framework specifically designed for Thai academia. It provides a framework for leaders aiming to foster sustainable and reliable institutional cultures in the age of artificial intelligence.

1.1. Research Objectives

The following goals guide this research: The primary objective is to create a predictive model employing sophisticated machine learning techniques to evaluate the level of institutional engagement and trust among faculty and support staff at Bangkokthonburi University. The model's goal is to capture complex behavior patterns and make organizational diagnostics more accurate.

The second objective seeks to examine and rank the principal factors influencing organizational commitment and trust, employing feature selection and model interpretability techniques to achieve a deeper understanding of the determinants of organizational commitment.

The third objective is to assess the proposed model's performance regarding accuracy, interpretability, and fairness through a comparative analysis of various algorithms, including logistic regression, support vector machine, k-nearest neighbors, decision trees, and Naïve Bayes, employing cross-validation to strengthen the research methodology's robustness.

In the end, the research aims to provide data-driven suggestions for managing human resources in higher education. These suggestions are meant to boost organizational commitment, build trust in institutions, and support the Sustainable Development Goals, especially SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth).

1.2. Research Hypotheses

The following hypotheses are posited based on the objectives and literature review.

Hypothesis 1 (H1) posits that organizational factors, such as leadership support, communication efficacy, career advancement opportunities, and the work environment, exhibit a statistically significant correlation with personnel commitment at Bangkokthonburi University. This underscores the significance of institutional structure and management practices as pivotal determinants of employee commitment.

Hypothesis 2 (H2) posits that heightened staff commitment is positively associated with increased levels of institutional trust among both faculty and support personnel, suggesting a synergistic relationship between individual dedication and institutional confidence.

Hypothesis 3 (H3) posits that machine learning models exhibit enhanced accuracy in forecasting levels of institutional engagement and trust in comparison to traditional statistical methodologies. This benefit comes from the fact that advanced algorithms can find complex relationships and non-linear patterns that traditional methods often miss.

Hypothesis 4 (H4) asserts that intrinsic motivational factors, including autonomy, recognition, and professional development, exert a more significant influence on institutional trust than extrinsic factors such as salary, workload, and welfare. This supports the notion that enduring trust is fundamentally anchored in internalized values rather than external circumstances.

Hypothesis 5 (H5) posits that the efficacy of machine learning models will exhibit considerable variability, with algorithms such as logistic regression, support vector machines, and k-nearest neighbors anticipated to attain superior accuracy and F1-scores relative to alternative algorithms.

1.3. Conceptual Framework

The conceptual framework delineates the hypothesized interconnections among organizational factors, personnel engagement, institutional trust, and the predictive function of machine learning models (refer to Figure 1). The research conceptual framework (Figure 1) illustrates the interconnection between organizational factors, employee engagement, and institutional trust, with machine learning models serving a crucial function in prediction and analysis. It is believed that organizational factors like leadership support, good communication, chances for career growth, and the work environment have a direct effect on how engaged employees are. As engagement rises, it is expected to foster enhanced institutional trust, which serves as the cornerstone for sustaining both academic excellence and administrative stability within universities.

At the same time, the framework includes both intrinsic and extrinsic motivational factors to explain why different people act differently. Intrinsic motivation, illustrated by autonomy, recognition, and professional development, is anticipated to have a significantly positive impact on engagement and trust. On the other hand, extrinsic factors like salary, workload, and welfare may have additional effects that depend on the situation. These variables are subsequently employed in machine learning models, such as Logistic Regression, Support Vector Machines, k-Nearest Neighbors, Decision Trees, and Naïve Bayes, to evaluate hypotheses, ascertain significant predictors, and gauge levels of engagement and institutional trust.

In addition to predictive accuracy, the framework emphasizes interpretability and fairness, making sure that insights can be turned into policies that can be put into action. This method helps higher education institutions use data to make decisions about their human resources, especially at Bangkokthonburi University's Faculty of Education and Faculty of Business Administration. The framework combines organizational psychology with artificial intelligence to create both an analytical tool and a practical guide for building trust and engagement in institutions. This helps Thai academia develop its human resources in a way that will last.

Conceptual Framework of Research

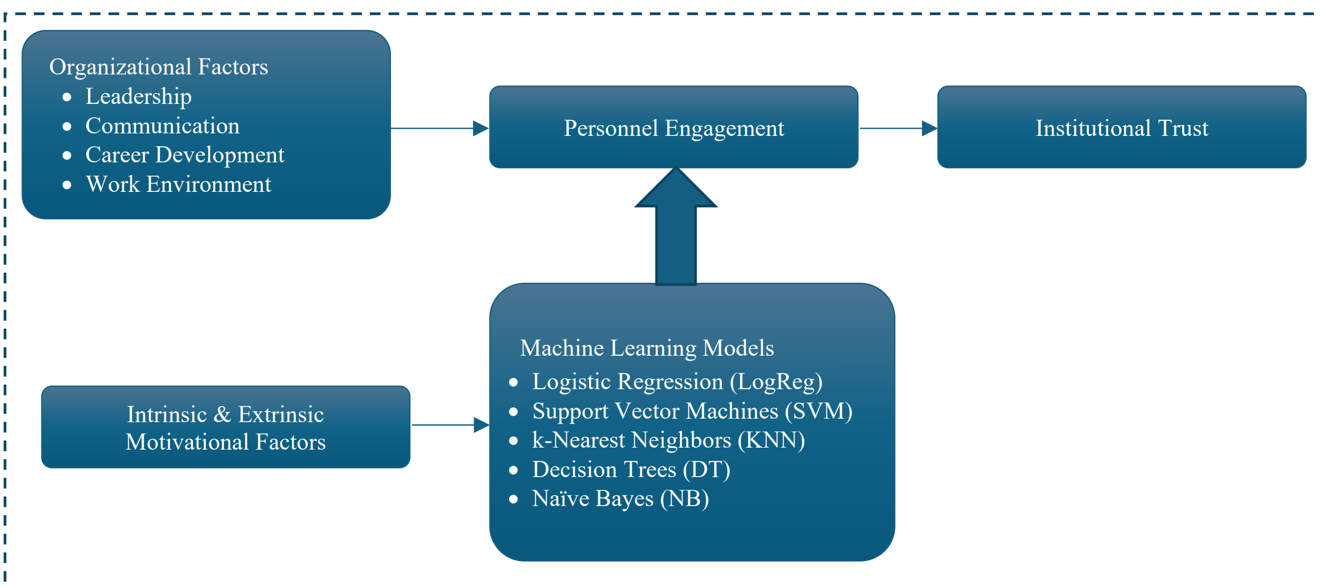

Fig. 1 Conceptual framework of research

1.4. Mapping of Research Hypotheses and Variables

Table 1. Mapping of research hypotheses and variables

Hypothesis	Statement	Independent Variables	Dependent Variables	Analytical Approach
H1	There is a statistically significant relationship between organizational factors and personnel engagement.	Organizational Factors (Leadership support, Communication effectiveness, Career development, Work environment)	Personnel Engagement	Correlation analysis, ML feature selection
H2	Higher levels of engagement are positively associated with higher levels of institutional trust.	Personnel Engagement	Institutional Trust	Regression analysis, ML classification
H3	Machine learning models can predict engagement and institutional trust with higher accuracy than traditional statistical methods.	Combined dataset of organizational and motivational factors	Engagement & Institutional Trust	Comparison of ML vs. statistical models
H4	Intrinsic motivational factors exert greater influence on institutional trust than extrinsic factors.	Intrinsic Motivation (Autonomy, Recognition, Professional growth) vs. Extrinsic Motivation (Salary, Workload, Welfare)	Institutional Trust	Feature importance, ML interpretability
H5	The predictive performance differs significantly across machine learning algorithms.	Machine Learning Algorithms (Logistic Regression, SVM, kNN, Decision Trees, Naïve Bayes)	Prediction Accuracy & F1-score	Cross-validation, model evaluation

The mapping table provides a concise correlation among the research hypotheses, variables, and analytical methodologies. H1 looks at how organizational factors affect employee engagement, while H2 looks at how engagement affects trust in the institution. H3 evaluates whether machine learning models exceed conventional statistical methods in predictive precision. H4 distinguishes the impacts of intrinsic and extrinsic motivational factors on institutional trust. Finally, H5 looks at how well different machine learning algorithms work. Together, these maps make up a coherent research framework that combines theoretical ideas with real-world data.

This study focuses on the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University in Thailand. It looks at the urgent need to understand and improve engagement and trust in institutions among higher education staff. The introduction points out that traditional HRM practices focus on external rewards, but long-term commitment to an organization needs internal motivation, trust, and active participation. The research seeks to examine the impact of leadership, communication, career development, work environment, and motivational factors on personnel engagement and institutional trust within a competitive and globalized academic context by merging organizational psychology with applied machine learning.

In line with this goal, the research objectives center on creating predictive machine learning models, pinpointing and prioritizing influential factors, assessing model accuracy and fairness, and providing data-driven HRM recommendations. The hypotheses indicate substantial correlations among organizational factors, engagement, and trust; a more pronounced impact of intrinsic motivation relative to extrinsic factors; and enhanced predictive efficacy of the chosen machine learning algorithms. The mapping framework connects each hypothesis to its variables and analytical methods, making sure that theory and real-world testing are in line with each other. These elements work together to create a strong base for improving HR analytics in higher education with the help of AI that is morally responsible.

2. Literature Review and Related Works

2.1. Motivational Factors in Higher Education

In Higher Education (HE), two main organizational outcomes have a big impact on performance and resilience: staff engagement and trust in the institution. Engagement means being energetic, dedicated, and focused on work tasks, while institutional trust means having faith in the university's ability, honesty, and kindness. Recent international studies agree on five key areas that universities can actively change: leadership, communication, career development, autonomy, and recognition. These areas are always linked to staff engagement and trust. Then, researchers put together about five years' worth of peer-reviewed studies to create a current conceptual basis for a survey in Thai higher education settings, like the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University, where academic and administrative roles overlap and make these levers even more important.

Leadership builds trust and gets people involved. Recent research on higher education leadership shows that how leaders lead is just as important as how they make decisions. Evidence from multiple nations indicates that when university leaders diminish hierarchies, delegate decision-making power, and foster secure environments that promote experimentation—especially with educational technology—they exemplify trust and, importantly, receive it in return. This mutual trust then encourages staff to take the initiative and come up with new ideas, which boosts their intrinsic engagement. On the other hand, giving someone else responsibility without enough support can lower motivation and trust. An open-access study that looks at eight European study programs [13] gives a full picture of these events. Moreover, a comprehensive scoping review of staff trust in higher education integrates global evidence, clarifying elements that cultivate trust, such as transparency in procedures and relational leadership, while underscoring results like collaboration and problem-solving, thus asserting that trust is a strategic asset within universities rather than merely a “soft” or secondary characteristic [14]. Leadership is also very important during stressful times. Studies of staff engagement during crises show that real, supportive leadership keeps people engaged by reducing uncertainty. This is something that institutions going through digital transformation and dealing with demographic changes need to think about.

Internal communication is the basis of trust within organizations and is an important part of building trust and confidence. In higher education, the quality of internal communication—characterized by clarity, timeliness, and bidirectionality—has been shown to forecast employee loyalty by enhancing job satisfaction and organizational engagement. A study published in a Nature-portfolio journal elucidates this relationship by employing a structural model that links internal communication with engagement, satisfaction, and loyalty, utilizing samples from higher education institutions [15]. A meta-review conducted in 2024 further corroborates that happiness-centered communication systems, encompassing recognition, well-being indicators, and voice channels, enhance trust signals and improve engagement outcomes across various sectors.

These results suggest possible design strategies that universities could adopt, including unit-level dashboards and dialogic updates [16]. Moreover, communication research views digital internal communication as a process for building skills that go beyond just sending messages. It supports strategies that include programs for developing human resources to keep people interested [17]. For faculties in Thailand with complicated administrative interfaces, these insights can be turned into useful design features, such as predictable communication flows, ways for students to give feedback, and clear explanations of workload and evaluation processes. Autonomy and self-determination promote enduring engagement. In diverse workplace contexts, a supportive environment where leaders reason, facilitate decision-making, and refrain from using controlling language consistently satisfies fundamental psychological needs, thereby increasing work engagement. A 2024 review in the journal Behavioral Sciences brings together recent empirical evidence from a variety of interventions. Teaching managers to promote autonomy improves employee need satisfaction, autonomous motivation, and engagement mechanisms, which are directly relevant to department and program leaders in higher education institutions [18]. In the realm of higher education, analyses grounded in Self-Determination Theory (SDT) underscore that autonomy, competence, and relatedness are essential motivators for academic success. Recent research published in the journal HERD explicitly incorporates autonomy within the context of higher education, underscoring its importance for sustained engagement in a dynamic work environment.

Career development is profoundly interconnected with engagement via exchange processes [19]. How people see the growth paths that are open to them also has a big effect on how engaged they are. This connection is evident in various sectors; recent evidence suggests that career advancement, encompassing skills enhancement and promotional opportunities, enhances commitment and emotional engagement via social exchange mechanisms. The idea that "universities invest in their employees, and employees give back by working hard" shows this. This model has been shown to be very strong and useful for knowledge workers, especially in the context of academic and professional careers at Thai universities.

Recognition encourages people to get involved and builds trust. It is important to understand that recognition is not just a surface-level thing; it gives them useful information. A thorough, extensive analysis performed in 2025, encompassing multiple cohorts (N = 25,285) and published in the journal PLOS ONE, illustrated that recognition and fairness substantially enhance engagement. Additionally, the quality of leadership not only enhances engagement but also reduces burnout, offering substantial evidence that structured recognition programs function as engagement catalysts and trust indicators when regarded as fair [20].

The integrated perspective and research gaps indicate a cohesive mechanism through which leadership behaviors, such as authenticity, engagement, and coaching, cultivate an internal communication environment defined by transparency and clarity [21]. These behaviors, along with clear signs of career growth and practices that encourage independence, lead to feelings of recognition that are both perceived and earned. These conditions foster institutional trust, resulting in heightened engagement and resilience. Recent studies in higher education advocate for the examination of these connections, particularly within national systems and across faculties. Thailand's higher education system strikes a balance between academic freedom, quality assurance, and limited resources, with a strong emphasis on teaching, networking, and Key Performance Indicators (KPIs).

2.2. Machine Learning in Human Resource Analytics

In academic settings, human resources analytics has swiftly evolved from dashboards to predictive and prescriptive models that anticipate engagement, turnover, and trust. Recent international studies demonstrate that standard algorithms, including logistic regression, support vector machines, random forests, gradient boosting, and k-nearest neighbors, can be customized to institutional data to pinpoint at-risk staff and elucidate organizational factors contributing to these risks, such as workload balance, recognition, autonomy, and managerial climate. The field is now focusing on explainability and responsible AI. This means that predictions should be able to be turned into fair and justifiable actions when it comes to sensitive decisions about people. Extensive evidence from 2022 to 2025 substantiates this strategic alteration [22-24].

A thorough review of the literature and high-performance case studies helps to improve turnover prediction and model transparency. This helps to set best practices for turnover modeling. A review spanning ten years, published in Expert Systems with Applications, catalogs more than twenty machine learning techniques employed for turnover prediction and evaluates their performance trends, highlighting the efficacy of tree ensembles and gradient boosting methods in attaining high accuracy. The review also warns about problems with human resource data, such as class imbalance and covariate shifts. The 2025 study in Expert Systems with Applications builds on this by using new models with ex post explanation features, like SHAP. These models not only rank risk factors, but they also make it clear how they affect things, whether they are helpful or harmful. This is important for planning HR interventions. These references give useful advice on how to do things: start with a good baseline model, like normalized logistic regression; compare it to a representative sample; adjust the probabilistic outputs; and make sure that both local and global explanations are ready before deployment [24].

In the realm of workforce engagement and satisfaction, while the predominant focus on machine learning in higher education has been on student analytics, nascent research is employing analogous methodologies to workforce outcomes. A recent study in Frontiers in Education employed feature selection methods in conjunction with five machine learning algorithms to ascertain principal predictors of job satisfaction among school leaders, a workforce in the education sector that shares comparable role requirements with university academics and administrators. This methodology demonstrates that effective feature selection, when integrated with a comparative analysis of models such as RF, CART, HGB, XGBoost, and LightGBM, produces interpretable determinants of engagement and satisfaction, with direct relevance to university human resources, particularly for department heads and program chairs [25].

From "Black Box" to Trusted HR Analytics: Responsible Use Is Now Mandatory. A qualitative study published in Technological Forecasting & Social Change in 2024 investigated end-user adoption of ML-based HR analytics, revealing that transparency, perceived fairness, and controllability affect usage intentions. The 2024–2025 study, on the other hand, found that algorithmic fairness was one of the most important performance criteria. Research in business analytics shows how bias can happen, which metrics to keep an eye on, and how to make things fairer without losing the benefits of automation. For university HR, where choices have an impact on careers, health, and academic freedom, these results show how important it is to have strict protections: (i) reporting equity metrics alongside AUC, (ii) human-in-the-loop review, and (iii) saving model cards [26, 27].

Explainability in an educational context, where evidence from education-focused artificial intelligence research indicates that the design of explainability can influence stakeholders' perceptions of trust and fairness. Khosravi et al. present XAI-ED, an explainability framework encompassing stakeholders, explainability objectives, and interface styles in their work "Computers & Education: Artificial Intelligence." Their design philosophy, which employs straightforward global models for high-risk scenarios, localized counterfactuals for enhanced actionability, and user-centric interfaces, is primarily centered on learning analytics but can be seamlessly adapted for human resources dashboards utilized by deans and HR personnel. These insights, when used with ESWA directional analysis, help stakeholders come up with model-driven but easy-to-understand ways to get involved and intervene [24, 28].

Lastly, the synthesis and gap review findings show that recent research shows that responsible processes include (1) addressing and removing bias in HR data, (2) comparing benchmarks and interpretable samples, (3) combining SHAP/LIME with reason codes, (4) assessing fairness, privacy, and changeability, and (5) adding human oversight. What is still not well understood, especially for people who work in higher education, is how to test engagement and exit models over time across different faculties and schools, as well as how data-driven interventions affect outcomes. Southeast Asian universities, such as those in Thailand, are strategically positioned to furnish multi-source evidence to address this gap [22, 26].

2.3. Sustainable HRM in Thai Universities

Sustainable Human Resource Management (SHRM) is becoming more and more important as a link between the performance of an organization and the United Nations

Sustainable Development Goals (SDGs). This shows that it is important to find a balance between long-term economic, social, and environmental outcomes. Contemporary SHRM research emphasizes practices such as equitable hiring processes, capacity building, and ethical governance that transcend conventional strategic HRM, promoting employee well-being and bolstering institutional legitimacy. Recent theoretical advancements and significant empirical evidence demonstrate that sustainable HRM practices improve employee resilience, engagement, and performance, which are critical determinants influencing service quality and research productivity in Higher Education Institutions (HEIs) [29].

The Sustainable Development Goals (SDGs) agenda has moved from being a vague signal to being a real, measurable part of higher education. A scholarly examination in this domain reveals that universities are formulating metrics that explicitly link SDG-aligned initiatives—namely, SDG 4, “Quality Education," and SDG 17, “Partnerships for the Goals"—to institutional processes, encompassing personnel management. Consequently, human resources functions must develop policies regarding hiring, development, evaluation, and engagement that can be objectively assessed against SDG indicators, rather than simply conforming to general Corporate Social Responsibility (CSR) requirements [30]. Moreover, Greater Health and Safety Management (GHRM), the environmental sector of Strategic Human Resource Management (SHRM), has shown a positive link with university sustainability performance through means such as innovation and the promotion of a green culture, thus offering a relevant avenue for incorporating sustainability science and practices into university functions and scholarly pursuits [31].

Globalization and the digital transformation have two effects on HR management in schools. A well-defined digital HR strategy that integrates HR processes with data, analytics, and automation tools has been demonstrated to enhance organizational performance. This strategic approach is different from the occasional use of e-HRM tools. Its goal is to help universities make the switch to digital transformation, which will lead to better-informed workforce development, career paths, and performance systems [32]. Conversely, heightened digital intensity may elevate job demands and psychosocial risks if workload design and psychosocial safety are neglected. Studies on burnout in higher education underscore this risk and endorse prevention-oriented strategies integrated within HR policies [33].

Burnout has now been proven to be a problem in Thailand's higher education system, where teachers have to do research, teach, get involved in the community, and handle administrative tasks. A 2025 study published in BMC Public Health, which surveyed 410 university lecturers from the region, revealed a significant incidence of burnout and established a correlation between emotional exhaustion and variables such as age and daily work hours. Moreover, diminished personal fulfillment correlated with salary levels, suggesting the possible impact of human resource policies on workload oversight, mentorship, and pay equity. These findings support the assertion that Strategic Human Resource Management (SHRM) should prioritize job resources, such as constructive feedback, social support, and access to mental health services, to alleviate the effects of elevated job demands [34].

Keeping staff is still a big problem for university human resources systems. Current evidence suggests that faculty retention improves when the HR environment promotes organizational trust and commitment through fair compensation, clear recruitment processes, and dependable performance management—factors deemed critical in Strategic Human Resource Management (SHRM) for institutions vying globally for talent. This change in the organizational climate is a strategic addition to missions that are in line with the Sustainable Development Goals (SDGs) and the growth of digital HR skills [35].

In the end, AI-powered human resources analytics in higher education makes it more powerful and more accountable. Recent studies show that AI-driven insights can help with long-term HR management by making processes more efficient and helping people make better decisions. However, this is only possible if institutions have strong ethical governance and a culture of readiness. This is in line with the main goal of Strategic Human Resource Management (SHRM): technology should help achieve long-term goals of fairness, openness, and human potential, not just short-term goals of performance [36].

A synthesis of the literature review on Thai universities has revealed significant alignments between the faculties of education and business administration within Bangkok's competitive ecosystem. These technological advancements suggest a consistent Strategic Human Resource Management (SHRM) approach, encompassing (i) HR indicators aligned with the Sustainable Development Goals (SDGs), (ii) workload and wellness policies designed to prevent burnout, (iii) a trust-building HR climate aimed at staff retention, (iv) green HR management strategies to align university operations and academic culture with sustainability principles, and (v) a digital HR strategy, including ethical artificial intelligence, to ensure these commitments are scalable and accountable. All of these strategies help schools stay competitive while still following the social contract of higher education [29, 30, 32].

3. Materials & Methods

3.1. Population and Sampling Methodology

Study setting and target population. The research was carried out at two academic units within Bangkokthonburi University (BTU)—namely, the Faculty of Education and the Faculty of Business Administration. The target population included university personnel from these faculties, comprising academic staff such as lecturers, assistant professors, and their equivalents, as well as administrative and technical support staff. The final sample consisted of 70 personnel selected from these faculties. Finding the sample size and sampling frame. The official staff lists kept by the two faculties made up the sampling frame. The sample size (n=70) was determined using the Krejcie & Morgan sampling table, a well-established technique for ascertaining a suitable sample size when the population (N) is known.

To guarantee the inclusion of essential subgroups, the researchers employed proportionate stratified sampling, categorizing the sample into two groups: (i) faculty affiliation, distinguishing between education and business administration, and (ii) employment type, differentiating between education and support staff. Simple random sampling was used to choose participants in each group based on how many of faculty members in that group. This method enhances representativeness and diminishes sampling error in a heterogeneous population when contrasted with simple random sampling.

The selection and exclusion criteria include all permanent salaried staff from both faculties during the study period, including those in academic and support roles. The criteria include employees, interns, and people who are on long-term leave. These criteria are meant to suggest a stable workforce, which is very important for making decisions about human resource policy.

An official circular asking for cooperation was sent out through the faculty's executive board and internal learning-exchange activities, like annual planning sessions. This helped with recruitment and reducing nonresponse. To get as many people to fill out the questionnaires as possible and to cut down on the number of people who didn't respond, they were filled out and turned in during planned organizational activities.

The researchers took ethical issues into account, and all participants were fully informed of the research goals and willingly gave their written consent. Responses were kept completely private and only used for academic research.

To guarantee the representativeness of the data and to mitigate potential limitations, the researchers stratified the sample by faculty and support role to include essential subgroups, such as academics and support staff, thereby facilitating comparisons among these subgroups as indicated in the study findings. The sample size (n=70) met the predetermined adequacy criteria; however, caution is warranted when extrapolating findings beyond the two faculties represented. In cases of unequal sample sizes, post-stratification weights can be utilized to reduce bias in estimation. This study employed a 5-point Likert scale for measurement, and responses were analyzed using descriptive and inferential statistical techniques. We checked the instrument's validity and reliability by looking at the IOC values, which ranged from 0.67 to 1.00, and the Cronbach's alpha coefficient, which was 0.95.

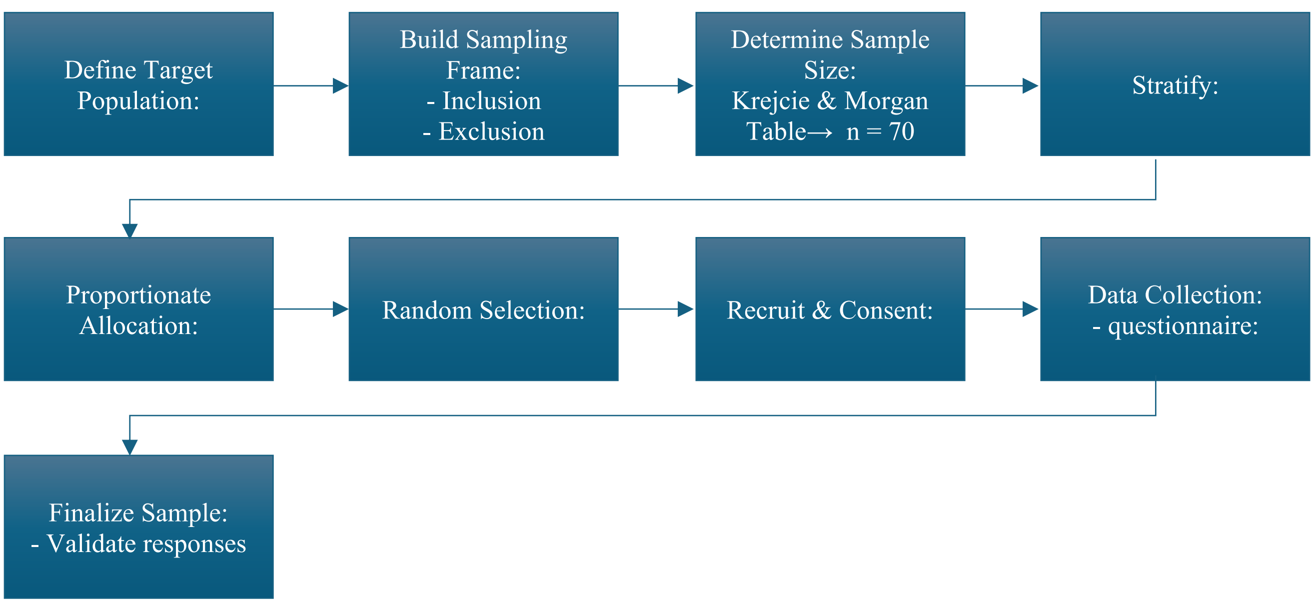

Fig. 2 Population and sampling methodology

3.2. Research Instruments

This study utilized a comprehensive four-component instrument, precisely calibrated to its analytical objectives, to model staff engagement and institutional trust—two outcomes that collectively define the university's organizational commitment profile among personnel of the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University. To begin with, a structured questionnaire was used to gather information on (i) organizational and motivational factors, such as leadership support, internal communication, career development, work environment, autonomy, and recognition, using five-point Likert scale items, and (ii) the two main outcomes, engagement and institutional trust, on similar scales.

This method made it easier to make composite indices and then do statistical and machine learning analyses. Second, a panel of three experts looked at the content validity by checking how well the items fit with the research goals. The Index of Item-Objective Congruence (IOC) ranged from 0.67 to 1.00. A pilot administration exhibited substantial internal consistency (Cronbach's alpha = 0.95), thereby meeting recognized validity and reliability criteria for organizational research instruments.

Third, we define a short and validated set of machine learning algorithms that work well with small to medium-sized institutional datasets and provide clear decision support. These algorithms include logistic regression, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), decision trees, and naïve Bayes. Standard linear regression is exclusively utilized for modeling continuous indices or calibrating probability scores. These algorithms are well-supported in human resource analysis for predicting turnover and engagement rates. Recent studies and applications suggest commencing with a normalized logistic baseline and contrasting it with a tree-based sample or margin-based learner, succeeded by an explanatory technique such as SHAP before implementation [23, 24].

Fourth, the dataset was divided into training and testing sets (80:20) to estimate generalization performance and prevent overfitting in a supervised learning setting. The 80:20 split is a well-established, widely used hold-out method, with alternatives like cross-validation available for robustness checks [37, 38]. Model quality was mainly evaluated using the confusion matrix, which produced metrics such as accuracy, Precision (PPV), Recall (TPR), and F1-score.

Accuracy offers an overall correctness measure; precision reflects false-positive control; recall assesses coverage of actual positives; and F1-score, the harmonic mean of precision and recall, acts as a balanced indicator, particularly important in the context of class imbalance often seen in organizational datasets [39, 40]. This evaluation approach, combined with an emphasis on interpretability and fairness as recommended in current HR analytics and operations analytics literature, ensures that predictions can be translated into auditable and ethically sound actions within academic HR decision-making [26, 27].

Table 2. Machine learning techniques

ML Techniques	Types	Purpose	Example
1. Linear Regression	Supervised learning (Regression)	Predicts a continuous output variable based on one or more input features by fitting a straight line (linear relationship).	Predicting house prices based on square footage.
2. Logistic Regression	Supervised learning (Classification)	Estimates the probability of a binary outcome (0 or 1) using a logistic (sigmoid) function.	Predicting whether an email is spam or not.
3. Decision Trees	Supervised learning (Classification and Regression)	Splits the data into branches based on feature values to make decisions. Easy to interpret.	Classifying loan applicants as low or high risk based on income, age, etc.
4. Support Vector Machines (SVM)	Supervised learning (Classification and Regression)	Finds the optimal hyperplane that best separates data into classes, especially effective in high-dimensional spaces.	Classifying handwritten digits or detecting cancer.
5. k-Nearest Neighbours (kNN)	Supervised learning (Classification and Regression)	It classifies a data point based on the majority class among its closest neighbours.	Recommending products based on similar users' preferences.
6. Naïve Bayes	Supervised learning (Classification)	Uses Bayes' Theorem, assuming features are independent. Fast and effective, especially for text classification.	Sentiment analysis of movie reviews.

3.3. Utilization of Statistics and Data Collection

The analysis employed both descriptive and inferential statistics to examine and forecast commitment-related outcomes—quantified as personnel engagement and institutional trust—among the staff of the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University (BTU). Descriptive statistics, including percentages, means, and standard deviations, encapsulated central tendencies and variability among constructs. The study utilized independent-samples t-tests and one-way ANOVA for inferential analysis to compare mean scores among groups (e.g., faculty, employment category), employing $\alpha = 0.05$ as the significance threshold. Before analysis, assumptions were checked in line with current best practices. For small n, the Shapiro–Wilk test checked for normality, and for $n \geq 50$, the Kolmogorov–Smirnov test with

Lilliefors correction checked for homogeneity of variance. When needed, robust options like Brown–Forsythe and Fligner–Killeen were used. Welch's correction was used to compare means when heteroscedasticity was found. These procedures adhere to contemporary guidelines for the selection and validation of parametric tests, as well as for mitigating inflated error rates when assumptions are violated [41-43].

A structured questionnaire was used to gather data from 70 staff members across the two BTU faculties to find out what organizational and motivational factors affect engagement and trust in the institution. Items utilized a 5-point Likert scale (1 = strongly disagree … 5 = strongly agree). To make the reporting clearer, the study used a standard five-band classification of mean score ranges: 4.21–5.00 (very high), 3.41–4.20 (high), 2.61–3.40 (moderate), 1.81–2.60 (low), and 1.00–1.80 (very low). This is a scheme that has been used in recent educational research. To make it easier to implement in the field and get the most responses, participation was requested through an official circular signed by the university's executive board and included in internal learning activities (like annual planning sessions), with collection on-site during scheduled organizational events. We used the dataset to train and test predictive models of outcomes related to commitment, in addition to traditional inference. To get a fair evaluation, we used confusion-matrix metrics like accuracy, Precision (PPV), Recall (TPR), and F1-score, especially when there was a chance of class imbalance [39].

4. Results

4.1. Demographic Information

The examination of demographic characteristics was structured around four variables—gender, age, educational attainment, and employment status—to delineate a precise profile of the study population (n = 70). We provide frequencies (n) and percentages (%) for each variable, and when appropriate (e.g., grouped age ranges), we also include measures of central tendency and dispersion to make the data easier to understand. Tables 3–6 (Table 3: gender; Table 4: age; Table 5: educational attainment; Table 6: employment status) show the descriptive results in a clear way. This will make it easier to compare and model subgroups in the future. If there are any missing responses, they are marked and summarized using a valid percent to make sure that the denominators are clear.

Table 3. Respondent information categorized by gender

Gender	Numbers	Percentage
Male	41	58.60%
Female	29	41.40%
Total:	70	100.00%

Table 3 displays the gender distribution of the sample (n = 70): male = 41 (58.60%) and female = 29 (41.40%), suggesting a predominantly balanced group with a marginal male predominance. We interpret this as a descriptive characteristic of staff composition within the two BTU faculties, rather than a universal trend across academic disciplines, as gender distributions in higher education differ based on institutional and disciplinary contexts. Recent evidence indicates that gender influences motivation, leadership perceptions, and associated attitudes within academic contexts. For instance, a 2024 study of university faculty reveals significant gender disparities in perceptions of transformational and transactional leadership, which impacts motivation and engagement. Consequently, it is imperative for analysts to regard gender as a potential moderating variable in the examination of commitment-related constructs [44].

Recent extensive research conducted in European universities highlights gender-specific disparities in job satisfaction and stress exposure among academic personnel, taking into account contextual nuances. This highlights the necessity of presenting gender-stratified descriptive statistics before undertaking inferential tests concerning involvement or organizational commitment [45]. Longitudinal studies of labor markets indicate gender-specific career trajectories in certain fields, particularly in STEM disciplines, suggesting that observed gender balances may be shaped by field-specific pipelines rather than universal effects. This is yet another reason to be careful about drawing conclusions from just one sample [46].

Table 4. Respondent information categorized by age

Age	Numbers	Percentage
Ages 30 to 35 years	6	8.60%
Ages 36 to 40 years	22	31.40%
Ages 41 to 45 years	28	40.00%
Aged 45 and older	14	20.00%
Total:	70	100.00%

Table 4 shows the ages of the people who answered the survey and shows that there are a lot of mid-career people in the workforce. The biggest group was 41 to 45 years old (n = 28; 40.00%), and the second biggest group was 36 to 40 years old (n = 22; 31.40%). The smallest group was 30 to 35 years old (n = 6; 8.60%). The other participants (n = 14; 20.00%) were not in these main age groups. In general, 71.40% of the sample is made up of people between the ages of 36 and 45. This suggests that the study mostly shows the opinions of people who have a lot of experience, procedural knowledge, and responsibility in the organization. When analyzing subsequent findings regarding engagement and organizational commitment, it is crucial to regard age as a contextual variable: contemporary studies indicate that work engagement generally escalates with age, and age affects the relationship between job resources and demands on engagement, thereby influencing motivation and loyalty within organizations. Moreover, research in higher education indicates age-related disparities in turnover intentions among academic personnel, underscoring the necessity of providing age-stratified data prior to making inferences regarding involvement, commitment, and retention [47, 48].

Table 5. Respondent information categorized by education level

Education level	Numbers	Percentage
Bachelor's Degree	12	17.14%
Master's Degree	32	45.72%
Doctorate Degree	26	37.14%
Total:	70	100.00%

Table 5 shows that most of the people who answered the survey have master's degrees (32, or 45.72%), followed by those with doctoral degrees (26, or 37.14%) and bachelor's degrees (12, or 17.14%). This is common in research-heavy colleges and universities, and it shows that there is a lot of specialization, formal research training, and different role expectations depending on the level of qualification. Prior studies conducted in universities have demonstrated that educational attainment is not a neutral metric; rather, it correlates with distinct patterns of organizational commitment and employee retention. A cross-university study revealed that faculty education substantially influenced commitment, indicating that certain cohorts of PhD graduates exhibited diminished organizational commitment compared to their less qualified counterparts. This corresponds with the "overqualification" trend observed in larger public sector samples. These trends may diminish affective commitment and elevate turnover intentions when role autonomy, recognition, and development support are misaligned with advanced educational qualifications [49].

Besides commitment, the qualification level also relates to professional identity and autonomy expectations. A systematic review of the literature demonstrates increased decision-making ability among professionals and academics, while an international study shows evolving role demands. This may limit or require greater academic autonomy. When institutions actively promote identity, autonomy, and support systems such as leadership, workload management, mentoring, trust, and commitment, they tend to strengthen these areas. Without such support, high qualifications can make staff more vulnerable to cultural mismatches and a lack of support [50, 51]. Overall, the distribution presented here suggests a group ready for high participation, provided that institutional practices meet staff needs for autonomy, recognition, and meaningful professional growth [52].

Table 6. Respondent information categorized by personnel type

Personnel type	Numbers	Percentage
Academic staff	50	71.40%
Support staff	20	28.60%
Total:	70	100.00%

Table 6 shows that 71.40% (n = 50) of the sample were academic staff and 28.60% (n = 20) were support staff. This means that the study's findings mostly show the views of academic staff. This is in line with the school's academic mission, where teaching, research, and academic service duties are closely linked to professional autonomy and academic identity. These are two things that have been linked to commitment and engagement in higher education. Recent studies indicate that autonomy and associated psychological needs affect academic motivation and commitment, implying that role-specific resources must be taken into account when analyzing commitment scores and formulating engagement strategies [53, 54].

Recent studies comparing academics and support staff indicate that workplace factors such as fairness, inclusion, psychological safety, and support for work-life balance are correlated with varying levels of organizational commitment within these groups. For instance, psychological safety usually has a bigger effect on academics' affective and normative commitment, while fairness and WLB support help both roles [55].

These differences align with the Job Demands-Resources (JD-R) model, which suggests that role-specific resources like autonomy, recognition, and coworker support enhance engagement and, consequently, commitment [56]. Importantly, the smaller (but essential) presence of support personnel should not be overlooked. Systematic literature reviews and sectoral analyses show that professional staff contribute strategically and increase knowledge, which boosts university performance and knowledge development, emphasizing the importance of role-based trust-building and career support mechanisms alongside academically focused interventions [56, 57].

4.2. Factors Influencing Personnel Engagement

Tables 7–10 illustrate organizational commitment as a multidimensional construct comprising four analytical components: (i) influencing factors, such as leadership, communication quality, and work environment, which shape employees' perceptions through resource pathways as delineated by contemporary Job Demands–Resources theory; (ii) belief in and acceptance of organizational goals and values, reflecting internalization and identification with the university's mission and norms; (iii) willingness to invest effort, signifying motivated and discretionary contributions to academic work; and (iv) desire to remain, indicating retention intent and attachment. Recent international academic research endorses this framework and its policy implications for higher education. To begin with, faculty commitment in higher education is clearly affected by organizational factors, such as trust, communication, and the climate for human resources. This shows how important it is to look at both internal and external factors when measuring success.

Second, making sure that identification fits with the goals and culture of the institution connects engagement and commitment in academic settings. Third, motivational efforts are linked to resourceful environments, such as those that promote autonomy, recognition, and support, which increase energy and commitment and provide useful paths for academic units. Lastly, the desire to stay is what drives strategic planning; commitment profiles can help predict retention, and evidence shows that fairness and the climate of human resources can affect faculty decisions. These four parts make up a data-driven framework for interventions like leadership development, better communication, and policies on workload and recognition that will help align culture with long-term commitment [56, 57].

Table 7. Factors impacting employees' commitment to the organization

Items	Means	S.D.	Interpretation
Perspectives on belief in and acceptance of the organization's goals and values.	4.04	0.72	High agreement
Perspectives on the willingness to put effort into working for the organization.	4.43	0.61	High agreement
Perspectives on the desire to continue as a member of the organization.	4.27	0.65	High agreement
Average:	4.25	0.66	High agreement

Table 7 shows that BTU staff have very positive views of organizational commitment, with a mean of 4.25 and an SD of 0.66. The most significant factor is willingness to exert effort, with a mean of 4.43 and a standard deviation of 0.61, consistent with Job Demands–Resources theory, which posits that resources such as autonomy and recognition enhance vigor, dedication, and commitment. Recent meta-analyses validate "work effort" as a quantifiable, commitment-related construct. The mean score for the desire to stay is 4.27, and the standard deviation is 0.65. This is because supportive HR climates and trust encourage people to stay by making them feel committed. However, the belief in and acceptance of organizational goals (mean 4, SD 0.72) exhibit variability, suggesting that values are not uniformly internalized. According to the literature, clearer communication of values and better communication within the organization can help people identify with the organization and be more committed to it, which can lead to more engagement and loyalty. Even though people are very committed, specific actions like value dialogues, leader sense-giving, and feedback can make things more stable and strengthen long-term commitment.

The data in Table 8 shows that most employees strongly believe in and accept the organization's goals and values. The mean is 4.04, and the standard deviation is 0.72. This shows that most people have a positive view, but there are some differences between people. The most highly rated factor was "acceptance of the corporate culture" (M = 4.10, S.D. = 0.75), which shows that most people liked the company's culture. Next came "confidence in organizational stability" (M = 4.06, S.D. = 0.72) and "recognition of personal growth opportunities" (M = 4.04, S.D. = 0.69).

The mean score for "faith in and endorsement of organizational goals and policies" was 4.03 (S.D. = 0.72). The lowest-rated factor, "perception of organizational values as suitable and worth following," got a score of 3.97 (S.D. = 0.72). The latter still shows a high level of agreement, but it also shows that communication and integration of organizational values need to improve.

Table 8. Factors impacting belief in and acceptance of the organization's goals and values

Items	Means	S.D.	Interpretation
The organization's values are appropriate and deserving of adherence and practice.	3.97	0.72	High agreement
One possesses confidence in the stability of this organization	4.06	0.72	High agreement
Faith in and endorsement of this organization's goals and policies.	4.03	0.72	High agreement
Confidence and discover opportunities for personal growth within this organization.	4.04	0.69	High agreement
Acceptance of the corporate culture of this organization	4.10	0.75	High agreement
Average:	4.04	0.72	High agreement

Overall, the results show that most employees agree with the organization's goals and rules. However, to get people to stay with the organization for a long time, it will be important to make strategic efforts to improve communication and instill core institutional values. Recent studies underscore the importance of effectively communicating organizational values and bolstering intrinsic motivation as essential for employee engagement and enduring organizational performance [58].

Table 9. Factors impacting willingness to invest effort in work for the organization

Items	Means	S.D.	Interpretation
Willingness to support the organization's activities in all aspects.	4.53	0.56	Highest agreement
A strong commitment to ensuring the success of the organization.	4.46	0.56	Highest agreement

A desire to fulfill responsibilities for the organization's benefit and to enhance its reputation.	4.44	0.61	Highest agreement
Dedication of knowledge and skills to duties, prioritizing the organization's interests above all.	4.41	0.60	Highest agreement
A readiness to sacrifice personal time for the organization's success.	4.29	0.71	Highest agreement
Average:	4.43	0.61	Highest agreement

Table 9 shows the results of the analysis, which shows the factors that make employees more likely to work hard for the company. The overall level of agreement is very high (M = 4.43, S.D. = 0.61). This shows that employees are very committed and consistent. The highest-rated dimension was "willingness to support the organization's activities in all aspects" (M = 4.53, S.D. = 0.56), which means that people were ready to get involved and fully participate in the organization's plans.

The second highest was "strong commitment to ensuring the organization's success" (M = 4.46, S.D. = 0.56), which shows that the person really believes in the organization's mission and goals. The third most important thing, "desire to fulfill responsibilities for the benefit and reputation of the organization" (M = 4.44, S.D. = 0.61), stresses being responsible and proud of making the organization look better.

At the same time, "dedication of knowledge and skills to duties, prioritizing organizational interests" (M = 4.41, S.D. = 0.60) shows a strong professional commitment to achieving institutional goals. The item with the lowest score, "readiness to sacrifice personal time for organizational success" (M = 4.29, S.D. = 0.71), is still in the very high agreement range, but it does show that employees may not be willing to give up their personal time for work purposes. In conclusion, employees show a strong intellectual and professional commitment to moving the organization forward, but work-life balance is still a major issue. Recent global research substantiates that cultivating intrinsic motivation and preserving work-life equilibrium are essential for sustaining employee engagement and organizational success [58].

Table 10. Factors impacting desire to continue as a member of the organization

Items	Means	S.D.	Interpretation
The organization's goals and ideology are identical.	3.94	0.70	High agreement
It is important to be loyal and honest when doing your job for the organization.	4.37	0.66	Highest agreement
This organization is the best place to work.	4.17	0.64	High agreement
The wish to remain a member of this organization endures.	4.44	0.61	Highest agreement
Communicating proudly with others about working in this organization is valuable.	4.43	0.63	Highest agreement
Average:	4.27	0.65	Highest agreement

The analysis of Table 10 examines the determinants affecting employees' inclination to remain with the organization, yielding an overall mean of 4.27 and a standard deviation of 0.65. This indicates a significant degree of organizational commitment. The dimension that got the most votes was "the wish to remain a member of this organization endures" (M = 4.44, S.D. = 0.61), which shows a strong long-term commitment and emotional connection to the organization. The second-highest item, "communicating pridefully with others about working in this organization is valuable" (M = 4.43, S.D. = 0.63), shows how important social identity and reputation are for keeping members. The third-ranked factor, "commitment to fulfilling duties with loyalty and honesty" (M = 4.37, S.D. = 0.66), shows how important it is to be honest and ethical as part of being dedicated to an organization. "This organization is the best place to work" (M = 4.17, S.D. = 0.61) shows positive feelings about the workplace, but not as strongly as the emotional and ethical dimensions. The item with the lowest rating, "the organization's goals and ideology are identical to mine" (M = 3.94, S.D. = 0.70), still has a high score, but it could mean that people and organizations are not on the same page. In conclusion, while emotional attachment and pride in membership are significant, focusing on strategic communication of shared goals and vision could further improve organizational retention. Recent international studies corroborate that cultivating organizational identity and aligning personal and organizational objectives through effective communication are essential for enhancing long-term commitment [58].

4.3. Factors Analysis Influencing Employee Engagement

The data analysis concerning factors influencing employee engagement within the organization was systematically categorized into four comparative groups: gender, age, educational background, and personnel type. We looked at each category to see if demographic factors had a big effect on how engaged employees were with the organization. This comparison helps us better understand how individual traits affect organizational commitment. This can help us come up with targeted engagement strategies for different groups of employees.

Table 11. Data analysis regarding factors categorized by gender

Factors Influencing Employee Engagement	Gender	N	Mean	S.D.	t	Sig
Perspectives on belief in and acceptance of the organization's goals and values.	Male	41	4.04	0.55	0.06	0.48
	Female	29	4.03	0.67		
Perspectives on the willingness to put effort into working for the organization.	Male	41	4.50	0.42	1.64	0.05
	Female	29	4.31	0.53		
Perspectives on the desire to continue as a member of the organization.	Male	41	4.26	0.40	-0.07	0.47
	Female	29	4.27	0.56		
Average:	Male	41	4.27	0.46		
	Female	29	4.20	0.59		
					1.64	1.01

Note: Statistical significance at the 0.05 level.

The comparative analysis in Table 11 investigated factors influencing organizational commitment among staff at the Faculty of Education and Faculty of Business Administration, Bangkokthonburi University, classified by gender. The results indicate that there were no statistically significant differences at the 0.05 level in the following domains: “belief in and acceptance of organizational goals and values,” “willingness to invest effort in organizational work,” and “desire to remain a member of the organization.” These results suggest that gender does not significantly influence perceptions of organizational commitment in this context. In other words, male and female staff members usually show the same level of commitment to the institution's values, success, and plans to stay connected with it. Recent international research corroborates this conclusion, emphasizing that organizational commitment is more significantly influenced by factors such as organizational culture and intrinsic motivation, rather than demographic variables like gender.

Table 12. Data analysis regarding factors categorized by age

Factors Influencing Employee Engagement	Group	SS	df	MS	F	Sig
Perspectives on belief in and acceptance of the organization's goals and values.	Among	1.57	3.00	0.52	1.50	0.22
	Within	23.12	66.00	0.35		
	Total	24.69				
Perspectives on the willingness to put effort into working for the organization.	Among	0.85	3.00	0.29	1.30	0.28
	Within	14.50	66.00	0.22		
	Total	15.35				
Perspectives on the desire to continue as a member of the organization.	Among	0.26	3.00	0.09	0.38	0.77
	Within	15.02	66.00	0.23		
	Total	15.28				
Average:	Among	0.89	3.00	0.30	1.05	0.42
	Within	17.55	66.00	0.27		
	Total	14.57				

Note: Statistical significance at the 0.05 level.

The comparative analysis in Table 12 evaluated the determinants affecting organizational commitment among staff at the Faculty of Education and Faculty of Business Administration, Bangkokthonburi University, classified by age group. The results indicated no statistically significant differences at the 0.05 level among the dimensions of “belief in and acceptance of organizational goals and values,” “willingness to invest effort in organizational work,” and “desire to remain as members of the organization.” These results indicate that organizational commitment does not exhibit substantial variation among different age groups. People of all ages showed the same level of commitment to the institution's values, success, and plans to stay with it. This consistency may indicate a common institutional culture or uniform organizational practices that promote engagement across generations. Recent global research corroborates this notion, demonstrating that organizational culture and institutional practices exert a more significant impact on commitment than demographic variables such as age.

Table 13. Data analysis regarding factors categorized by education level

Factors Influencing Employee Engagement	Group	SS	df	MS	F	Sig
Perspectives on belief in and acceptance of the organization's goals and values.	Among	0.28	2.00	0.14	0.39	0.71
	Within	24.40	67.00	0.36		
	Total	24.69				

Perspectives on the willingness to put effort into working for the organization.	Among	0.11	2.00	0.05	0.24	0.74
	Within	15.25	67.00	0.23		
	Total	15.35				
Perspectives on the desire to continue as a member of the organization.	Among	0.00	2.00	0.00	0.03	0.99
	Within	15.28	67.00	0.23		
	Total	15.28				
Average:	Among	0.13	2.00	0.07	0.21	0.82
	Within	18.31	67.00	0.27		
	Total	18.81				

Note: Statistical significance at the 0.05 level.

Table 13's comparative analysis looked at the factors that affect the commitment of employees at Bangkokthonburi University's Faculty of Education and Faculty of Business Administration, sorted by level of education. The results indicated no statistically significant differences at the 0.05 level in the dimensions of "belief in and acceptance of organizational goals and values," "willingness to invest effort in organizational work," and "desire to remain as members of the organization." These findings indicate that educational attainment does not substantially influence organizational commitment in this context.

People with bachelor's, master's, or doctoral degrees had the same feelings about the organization's mission, their work contributions, and their long-term ties to the organization. This result may suggest the existence of a robust institutional culture and uniform management practices that foster engagement among individuals from diverse educational backgrounds. Recent international studies corroborate this perspective, highlighting that organizational commitment is more significantly affected by organizational culture and the workplace environment than by demographic variables such as educational attainment.

Table 14. Data analysis regarding factors categorized by employee type

Factors Influencing Employee Engagement	Staff	N	Mean	S.D.	t	Sig
Perspectives on belief in and acceptance of the organization's goals and values.	Academic	50	4.09	0.61	1.15	0.13
	Support	20	3.91	0.56		
Perspectives on the willingness to put effort into working for the organization.	Academic	50	4.44	0.47	0.40	0.35
	Support	20	4.39	0.48		
Perspectives on the desire to continue as a member of the organization.	Academic	50	4.30	0.47	0.91	0.18
	Support	20	4.19	0.47		
Average:	Academic	50	4.28	0.52		
	Support	20	4.16	0.50		
					0.82	0.66

Note: Statistical significance at the 0.05 level.

Table 14 compared factors influencing organizational commitment among staff at Bangkokthonburi University's Faculty of Education and Faculty of Business Administration, divided into academic and support groups. Results showed no significant differences at 0.05 in 'confidence in and acceptance of organizational goals and values,' 'effort to serve the organization,' and 'desire to maintain membership.' This suggests both groups have similar commitment levels, reflecting a strong institutional culture or effective engagement strategies. The findings also suggest that policies and management foster trust, motivation, and loyalty among all staff.

4.4. Model Constructed

This research analyses data gathered from questionnaires filled out by 70 employees from the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University. The analysis centres on three principal dimensions of organizational commitment: (A) Trust and acceptance of the organization's goals and values, (B) willingness to put in effort for the organization, and (C) desire to stay with the organization (see Figure 3).

The first part, Trust and Acceptance of the Organization's Goals and Values (Factor A), has five sub-factors: A1: how appropriate the organization's values seem to be; A2: how confident people are in the organization's stability; A3: how well people accept the organization's goals and policies; A4: how well people see opportunities for personal growth within the organization; and A5: how well people accept the organization's culture.

The second aspect, Willingness to Invest Effort in the Organization (Factor B), includes five sub-factors: willingness to support organizational activities (B1), strong intention to contribute to organizational success (B2), responsibility-driven performance to boost the organization's reputation (B3), dedication of knowledge and skills in service of the organization (B4), and readiness to sacrifice personal time for organizational success (B5).

The third part, Desire to Stay with the Organization (Factor C), has five sub-factors: feeling like the organization's goals and values are in line with your own (C1), being loyal and honest to the organization (C2), thinking that the organization is the best place to work (C3), wanting to keep being a member (C4), and being proud to be a part of the organization (C5).

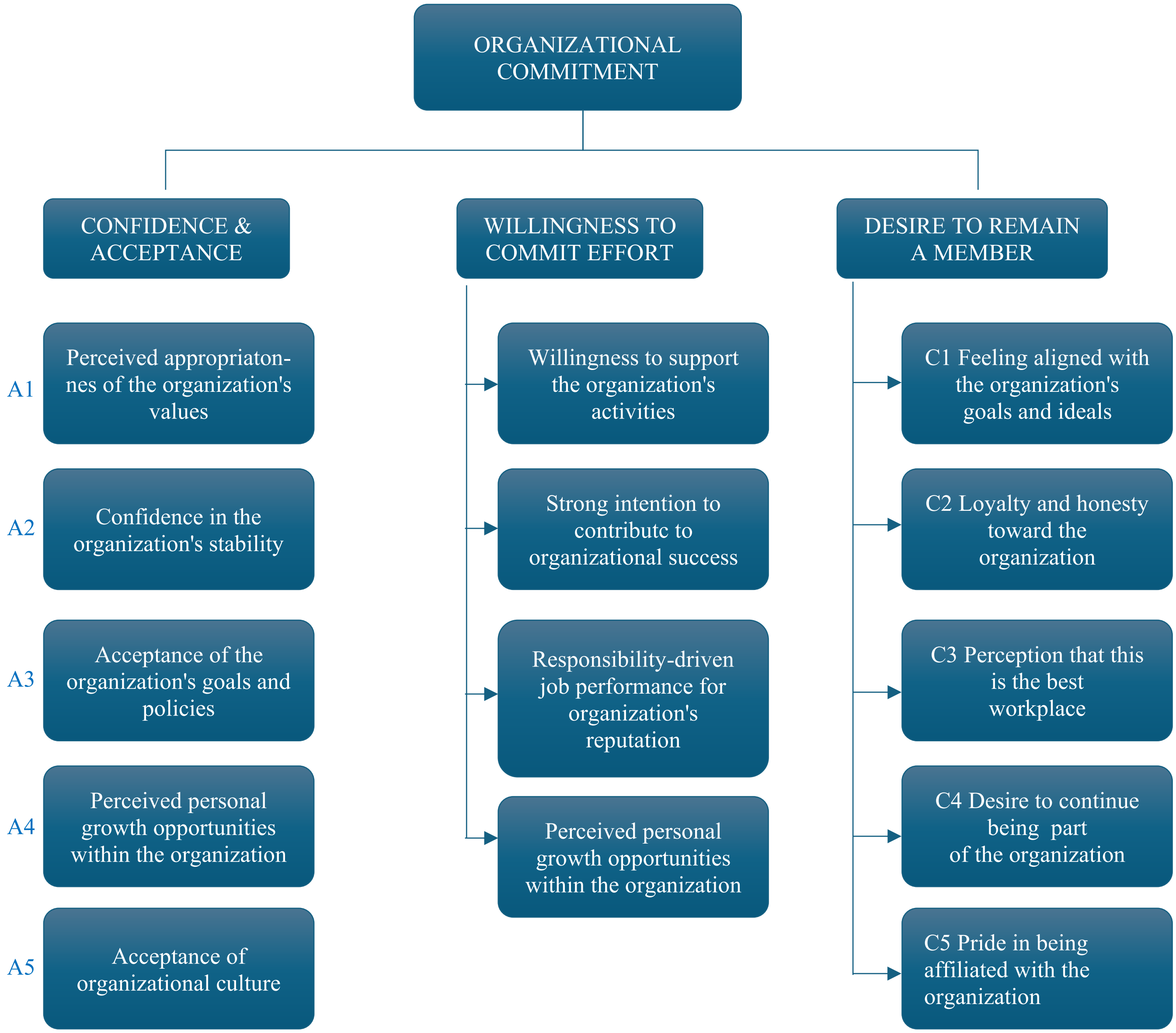

Fig. 3 Organizational values trust and acceptance model diagram

4.4.1. Overview of the Developed Clustering Model

The researchers used K-means Clustering, an unsupervised machine learning method, to group employees based on how loyal and confident they were in the organization before using the six supervised machine learning models. This method made it possible to find naturally occurring patterns and behavioural profiles in the dataset without using pre-defined class labels. The goal of the clustering process was to find patterns in the data and make groups that could be used as target classes for future predictive modelling.

Each cluster consisted of employees exhibiting analogous organizational attitudes—such as high loyalty/high commitment, low engagement, or at-risk groups—providing a significant foundation for subsequent human resource planning and organizational intervention.

Figure 4, Table 15, and Table 16 show the results of the clustering process. They show the most important characteristics of each cluster, such as the number of members, the average scores on organizational commitment dimensions, and some early behavioural interpretations.

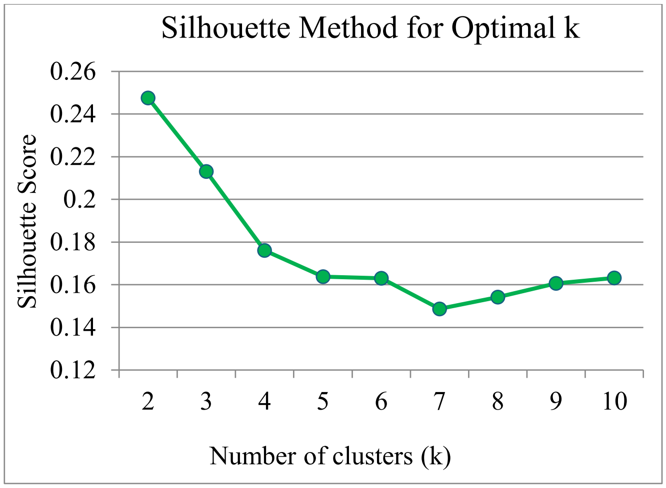

Fig. 4 Optimal cluster number chart by Silhouette

Table 15. Optimal cluster numbers according to the silhouette

k	Silhouette Score	
2	759.0115	0.2475
3	683.8282	0.2130
4	596.2790	0.1761
5	555.5625	0.1637
6	516.0339	0.1630
7	503.4613	0.1487
8	457.8947	0.1542
9	424.3945	0.1606
10	402.3867	0.1632

Figure 1 and Table 15 show that the highest Silhouette Score is 0.2475 at k = 2. This means that putting the data into two groups gives the best separation. When you add more clusters, the within-cluster error (like SSE) goes down, but the Silhouette Score goes down, which means that the groups are less distinct and may even overlap. All of the scores are still below 0.25, which means that there isn't a strong tendency for the data to cluster and that it might be more continuous than grouped. Researchers should therefore contemplate supplementary methodologies such as dimensionality reduction techniques (e.g., PCA, t-SNE) or alternative clustering algorithms like DBSCAN, which do not necessitate predetermined cluster counts, to more effectively elucidate the underlying structure of the data. Table 15 systematically summarizes the data and characteristics of members divided into two clusters. It gives a detailed picture of each cluster's unique traits and points out any statistically significant differences between the groups.

Table 16. Members per cluster and proportion

Cluster	Count	Percentage
cluster_0	27	38.57
cluster_1	43	61.43

The dataset was split into two groups, as shown in Table 16. Cluster_0 has 27 members (38.57%), and cluster_1 has 43 members (61.43%). This uneven distribution shows that the sizes of the clusters are not balanced, which could mean that the data naturally group themselves together. The difference in group sizes should be taken into account because it could affect future comparative analyses, especially when trying to find differences in behaviour or traits between clusters.

As shown in Table 17, six machine learning algorithms were used to process and analyse the collected data: Linear Regression, Logistic Regression, Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbours (kNN), and Naïve Bayes Classifier.

4.4.2. Overview of the Developed Classification Model

This study offers a summary of six machine learning models created to forecast organizational commitment trends utilizing structured questionnaire data. The models encompass both linear and non-linear methodologies, including regression, probabilistic, and instance-based techniques. We chose each algorithm because it was theoretically relevant, easy to understand, and had been shown to work in previous studies on employee behavior and organizational analytics. The main goal is to compare how well the predictions work, how strong they are, and how useful they are in the context of Thai higher education institutions.

The models employed include Linear Regression for discerning linear correlations between predictors and commitment levels; Logistic Regression for categorizing organizational commitment; Decision Trees, which provide comprehensible rule-based decision frameworks; Support Vector Machines (SVM), engineered to distinguish classes via hyperplanes with optimal margins; k-Nearest Neighbors (kNN), which forecasts outcomes based on proximity to similar data points; and the Naïve Bayes Classifier, which calculates class membership probabilities under the premise of conditional independence.

To make a fair comparison, all of the models were trained and tested on the same set of data. Table 16 shows the results of this model development. Recent studies emphasize that employing multiple algorithms for comparison enhances both predictive accuracy and the strategic insights accessible to HR and organizational decision-makers [59].

Table 17. Predictive model results using six techniques

Model	Accuracy	Precision	Recall	F1-score
5-Fold Cross-validation				
Decision Tree	0.8714	0.8757	0.8575	0.8598
k-NN	0.9143	0.9186	0.9142	0.9109
Logistic Regression	0.9571	0.9589	0.9489	0.9525
Naïve Bayes	0.9429	0.9509	0.9364	0.9357
SVM	0.9571	0.9589	0.9489	0.9525
10-Fold Cross-validation				

Decision Tree	0.8286	0.8258	0.8092	0.8075
k-NN	0.9571	0.9525	0.9525	0.9507
Logistic Regression	0.9429	0.9300	0.9300	0.9300
Naïve Bayes	0.9429	0.9525	0.9358	0.9334
SVM	0.9286	0.9200	0.9133	0.9144
	0.8286	0.8258	0.8092	0.8075

Table 17 shows how six machine learning algorithms—Decision Tree, k-Nearest Neighbors (k-NN), Logistic Regression, Naïve Bayes, and Support Vector Machine (SVM)—compare when tested with 5-fold and 10-fold cross-validation. We used Accuracy, Precision, Recall, and F1-score to measure performance. These metrics give a full picture of how well the models do at classification accuracy, completeness, and consistency. The 5-fold cross-validation showed that Logistic Regression and SVM were the best models, with an Accuracy of 0.9571 and an F1-score of 0.9525. These results show that they can strike a good balance between accurate positive detection (Recall) and fewer false positives (Precision). Naïve Bayes came in second with an F1-score of 0.9357, making it a good choice when speed and efficiency are important. On the other hand, the 10-fold cross-validation results show that k-NN did the best job, with an Accuracy of 0.9571 and a Recall of 0.9525.

k-NN gets better at making predictions when it is trained on different subsets. But Logistic Regression and Naïve Bayes gave stable results, with F1-scores of 0.9300 and 0.9334, respectively. Think about things like class imbalance, feature distribution, and size when working with a dataset. k-NN is sensitive to outliers and takes a lot of time to compute, so it can't be used in real time. On the other hand, Decision Trees have a lower accuracy (0.8286) but make clear, understandable decisions that are important for trust, regulation, and ethics.

Table 18. Comparative schematic of machine learning models

Category	Model	Key Characteristics
Linear Models	Linear Regression	Captures linear relationships between predictors and commitment level.
	Logistic Regression	Classifies organizational commitment into categorical outcomes.
	Naïve Bayes	Probabilistic model using conditional independence assumptions.
Non-Linear Models	Decision Trees	Rule-based, interpretable decision structure; handles non-linear patterns effectively.
	Support Vector Machines (SVM)	Separates classes with hyperplanes maximizing margins.
	k-Nearest Neighbors (kNN)	Predicts based on similarity to the closest data points.

The schematic table divides machine learning algorithms into two groups: linear and non-linear models. It shows how well they can predict organizational commitment. Linear Models encompass Linear Regression, Logistic Regression, and the Naïve Bayes Classifier, which are utilized for modeling simple, probabilistic, or classification tasks. Decision Trees, SVM, and kNN are examples of non-linear models that make predictions based on rules, proximity, and other factors. Linear models are better at being understandable, while non-linear models are better at finding complex patterns, which makes them more accurate and useful for predictions.

5. Discussion

The research findings on factors influencing personnel's organizational commitment at the University of Phayao are organized by the following objectives:

5.1. Regarding Organizational Commitment

5.1.1. Regarding Confidence and Acceptance of the Organization's Goals and Values

It was found that the staff of the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University had a strong opinion about what affects organizational commitment. The level of commitment among these employees is greatly influenced by how well they fit in with the company's culture. This acceptance shows that they believe in and support the institution's goals and values, which leads to pride, stronger connections, long-term loyalty, and good relationships with coworkers. To strengthen the bond between the organization and its members, it is important to show behaviours that are in line with the needs of the organization. The culture of an organization is very important in deciding what work should be done. When employees accept the company's culture, they are happier at work, work better together, are more flexible with the company's strategies and operations, and are more loyal.

5.1.2. Concerning the Willingness to Contribute Effort to the Organization

People who work at the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University have strong opinions about what makes people committed to their jobs. Their willingness to help with organizational activities is a big part of their commitment. It shows that they care about both personal and organizational goals and that they are actively involved in management. Employees' sense of responsibility toward themselves and the company is greatly improved when they take part in a variety of activities. It also helps people feel like they belong and own their place in the organization. So, when workers put in extra effort and are willing to help with company projects, it shows that they are very engaged. This involvement, in turn, helps the organization grow and reach its goals now and in the future.

5.1.3. Regarding the Aspiration to Maintain Membership within the Organization

The Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University had strong opinions on what makes people committed to their organizations. Their desire to stay with the organization was the most important thing that affected their commitment. This means that the staff felt like they belonged and were valued, which shows that they were happy with their work environment, had good relationships with their coworkers, had chances to learn and grow in their careers, and overall enjoyed their work life.

As shown by their desire to remain members, financial incentives and organizational benefits demonstrate the employees' dedication to the organization. This leads to organizational loyalty, enthusiasm for work, increased efficiency, and a lower personnel turnover rate [60].

5.2. An Examination of Perspectives Regarding the Factors Influencing Organizational Commitment

A comparative analysis of data regarding factors affecting the organizational commitment of personnel in the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University has been performed. This analysis categorizes personnel by gender, age range, educational attainment, and employment type. The research investigates three dimensions: 1) belief in and acceptance of the organization's goals and values, 2) willingness to put in effort for the organization, and 3) desire to stay a member. At the 0.05 level, the results do not show any statistically significant differences. The organization does a good job of communicating its values and goals, which builds trust and commitment among its employees. This makes them more likely to work together toward common goals and see chances to grow. The Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University make it very clear what each person's job is. Staff know how important it is to follow the organization's rules and vision, which includes making sure that everyone is paid fairly, has access to benefits, and has chances to help the organization grow. Because of this, employees feel like they are on the same page with the organization [61].

5.3. Discussion of Model Results

This research effectively illustrates the utilization of both unsupervised and supervised machine learning techniques to assess organizational commitment among university personnel. At first, K-means clustering was used to group employees based on how loyal and confident they were. Researchers discovered the peak Silhouette Score at k = 2 (0.2475), signifying feeble clustering tendencies and a continuous data structure. The findings indicate that subsequent research may gain from employing methodologies such as dimensionality reduction or density-based clustering techniques, such as DBSCAN, which are more effective with clusters of atypical shapes [62].

During the predictive modelling phase, Logistic Regression, SVM, and k-NN exhibited the highest accuracy and F1-scores (up to 0.9571), indicating their efficacy in identifying organized behavioural patterns. These findings are generally consistent with Li & Meng (2024), who evaluated various classifiers, including Logistic Regression, k-NN, Random Forest, and others, to predict job satisfaction among medical personnel in public hospitals in China, identifying Logistic Regression and k-NN as high-performing models, with Random Forest also recognized as a leading model [63].

But accuracy shouldn't be the only thing that determines which model to use. Models that are easy to understand are needed for practical use, especially in academic or institutional HR systems. Even though Decision Trees aren't as accurate (0.8286), they are more open and have logic that can be followed, which makes them better for ethical AI design. Ribeiro et al. (2016) stress that interpretable models help build trust and make sure people follow the rules, especially in fields that are sensitive, like education and work [64].

This research not only shows that AI can make predictions, but it also suggests a responsible and understandable AI framework for developing organizations in Thai higher education settings. It links technical performance to real-world limits, which will help machine learning be used in human resource planning in the future.

5.4. Recommendations for Future Research

Here are some suggestions for future research: First, it is important to look into the things that affect trust in an organization, with a focus on management skills, openness, and responsibility. Second, researchers should look into ways to increase organizational commitment by splitting study groups into executives and staff. Finally, there will be a thorough study of how employees affect their commitment to the organization.

6. Conclusion

This study thoroughly investigated the factors influencing organizational commitment and institutional trust among university staff, particularly within the Faculty of Education and the Faculty of Business Administration at Bangkokthonburi University. By combining statistical and machine learning methods, the study gave strong insights into the complex relationship between employee attitudes, organizational culture, and loyalty to the institution. From a descriptive standpoint, the findings validated heightened levels of consensus among personnel across all facets of commitment, especially regarding their readiness to exert effort and maintain affiliation with the organization. These findings corroborate previous studies highlighting the importance of active engagement and intrinsic motivation among individuals to maintain a high-performing organization. There were no statistically significant differences in demographic variables like gender, age, education, and type of employment. This shows that the institution's human resources policies are effective at promoting fair views of engagement and opportunity. This shows that the organization has a single identity and culture that goes beyond its structural divisions.The machine learning part of the study showed that both supervised (like Logistic Regression, Support Vector Machine, and k-Nearest Neighbours) and unsupervised (like K-means) methods worked well for sorting staff and guessing how engaged they would be. Even though the clustering process only got a Silhouette Score of 0.2475 ($k = 2$), the segmentation still gave a good behavioural framework for future predictive modelling. Logistic Regression and Support Vector Machine were the best classification models when tested five times, while k-Nearest Neighbours was the best when tested ten times. This means that these models are good for analysing organizations.

This study underscores the practical importance of model interpretability, in addition to its technical evaluation. Even though Decision Trees were less accurate, their clear reasoning supports the ethical use of AI in HR management, especially in sensitive areas like academia.

In conclusion, this study not only enhances the domains of educational data mining and AI-driven human resources analytics but also promotes a responsible and comprehensible framework for future decision-making processes. The proposed model offers a feasible approach for colleges and universities to enhance employee engagement and foster trust within their organizations by reconciling predictive accuracy with fairness and transparency.

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