The Effectiveness of Knowledge Management Systems in Improving Teaching Motivation among Vietnamese Higher Education Staffs

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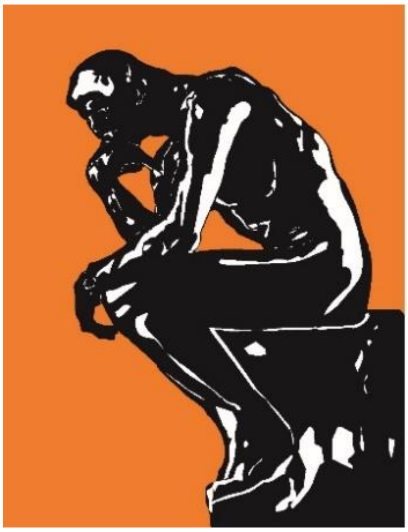

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"Today, Kingfisher the Wise teaches the most important lesson: "Wisdom in fishing"."

— In "The Weirdest Fishhook"; *The Kingfisher Story Collection* (2022)

Abstract

This study investigates the dynamic relationship between knowledge management systems, particularly emphasizing knowledge acquisition and dissemination, and their impact on academic staff's teaching motivation. By employing the Bayesian Mindsponge Framework (BMF), data from 676 academic staff at higher education institutions in Vietnam was analyzed, revealing a complex interplay of factors. Notably, positive associations were found between knowledge acquisition, knowledge dissemination, and teaching motivation. However, the interaction effect of knowledge acquisition and knowledge dissemination appeared to be negatively associated with teaching motivation. This suggests the possible existence of a resource curse of knowledge in improving staff's teaching motivation. It is recommended that the knowledge systems are refined to reduce complexity and that staff are trained with better knowledge processing methods for reducing resource curse risks.

Keywords: knowledge management systems, knowledge acquisition, knowledge dissemination, teaching motivation

1. Introduction

Vietnam's higher education (HE) system has radically transformed since the 1986 economic renovation (*Doi Moi* movement). Changing from a planned economy to a socialist market-driven economy has ignited the Vietnamese higher education institutions (HEIs) toward effective and efficient operations (Tran et al., 2023; Ngo & Le, 2024). Indeed, in the early 1990s, the Communist Party Vietnam Committee declared that education and training were the national priority for socio-economic development (Sheridan, 2010). A decade later, the Vietnamese government put forward Resolution 14/2005/NQ-CP on the comprehensive Vietnamese HE reform, namely the "Higher Education Reform Agenda" (HERA). HERA formulated the development agenda and strategy for Vietnamese education and research activities between 2006-2020 (Sheridan, 2010; Hayden & Le-Nguyen, 2020). In 2014, the Vietnamese government issued Resolution 77/NQ-CP, which announced the establishment of a pilot scheme toward institutional autonomy among HEIs (Tran et al., 2022; Do & Mai, 2022). Furthermore, the latest Law on Higher Education following the 34/2018/QH14 provides the HEIs with more financial and institutional autonomy and accountability. Lessening direct subsidies from the national government to public universities encouraged them to operate efficiently and effectively under the umbrella of the market mechanism.

Because of the challenges of the COVID-19 pandemic, social distancing is so necessary that teaching and learning on online educational platforms become popular not only in Vietnam but also worldwide. Hence, the information systems-based knowledge management (KM) practices seem beneficial in storing and sharing knowledge among educators and learners, particularly in Vietnamese HEIs (Nguyen, 2023; Pham et al., 2022). Secondly, in the wave of digital transformation, data-centered information technologies such as knowledge management systems (KMS) are necessary for business activities (Machado et al., 2022). Knowledge-based systems can facilitate boosting the learning process within organizations (Machado, 2022), leverage collective knowledge creation (Di Vaio et al., 2021; Pham et al., 2022), and improve the effectiveness and efficiency of operations (Alavi & Leidner, 2001). Consequently, KMS potentially increases individual and organizational performance (Ho, 2009; Pham et al., 2022) and sustains the competitive advantage (Alavi & Leidner, 2001; Machado, 2022; Di Vaio et al., 2021). In virtue of its benefits, KMS has garnered attention from practitioners and scholars in terms of technological and management viewpoints, particularly in higher education.

KMS refers to an information system (IS) that facilitates organizational knowledge's codification, collection, integration, and dissemination (Alavi & Leidner, 2001). The process of KMS in the organization includes the creation, storage and retrieval, distribution, and application of knowledge (Alavi & Leidner, 2001). In the digital era, KMS prompts the development of an open and collaborative ecosystem, boosting innovation capacity within organizations by exploiting data, information, and knowledge flows (Di Vaio et al., 2021). The application of KMS in educational settings has become popular in the recent decade (Dneprovskaya & Shevtsova, 2018; Nupap, 2022; Pinto, 2012).

In higher education, KMS can increase innovation, creativity, knowledge generation, and intellectual property development toward a knowledge-based economy (Pinto, 2012). Furthermore, Nupap (2022) stated that implementing KMS encourages academic staff to transform tacit knowledge into explicit knowledge and vice versa, creating an organizational learning atmosphere for long-term competitive advantage. KMS harnesses information technologies such as intelligent databases, networks, and co-authorship instruments to create knowledge value for innovative learning in the digital economy (Dneprovskaya & Shevtsova, 2018). Furthermore, the learning management system-integrated KMS could increase the quality of education by upgrading the curricula in real time and supporting educational materials to learners in e-learning platforms (Dneprovskaya & Shevtsova, 2018).

In the corpus of literature, few theoretical and empirical studies have examined KMS in the context of Vietnam's HE. For the qualitative approach, Nguyen (2023) emphasizes that deploying KMS in entire HEIs can foster the global integration of the Vietnamese HE system. KM practices can satisfy academic staff through a supportive working environment like sufficient facilities, infrastructure, or career promotion (Nguyen, 2023). On the other hand, for the quantitative approach, a study by Nguyen and Gregar (2018) shows significantly positive associations between knowledge acquisition, utilization, dissemination, and technical innovation. Only knowledge utilization positively impacts administrative innovation, but knowledge acquisition and utilization do not (Nguyen & Gregar, 2018). Another study indicated that knowledge management enablers at personal and organizational levels positively impact knowledge management processes and explain the gain of the university's performance in Vietnamese HEIs (Pham et al., 2022). Given the university's performance regarding human resources, Nguyen and Ha (2023) investigated the internal communication influencing academic staff engagement, satisfaction, and loyalty in Vietnamese HEIs.

Accordingly, the research on the links between KMS factors and academic staff satisfaction and motivation is still limited. To fill this gap, Bui and Tran (2023) provided a dataset of 676 academic staff in Vietnam HEIs on the knowledge acquisition, dissemination, and utilization impacting academic staff teaching motivation. These authors conducted the preliminary analysis using partial least square-structural equational modeling (PLS-SEM) and provided several insightful findings and implications. However, they could not indicate the dynamic impacts of KMS on the academic staff's teaching motivation. Therefore, our study aims to analyze these dynamics further using the Bayesian Mindsponge Framework (BMF), which is scarce in literature to the best of our knowledge.

The BMF analytics introduces an innovative research method for social and psychological research (Nguyen et al., 2022). The novel research framework is central to the integration of the Mindsponge mechanism's conceptual formulation and Bayesian inference for social, psychological, and behavioral phenomena (Nguyen et al., 2022; Vuong, 2023). BMF analytics seems to be a good fit for explaining the hypothesized links among KM practices and their relationship to academic staff's attitude and behavior.

Our purpose of this study is to fill the gap with the following research questions:

- Examine how knowledge acquisition and dissemination are associated with academic staff's teaching motivation.
- Examine how the interaction between knowledge acquisition and dissemination is associated with academic staff's job satisfaction and teaching motivation.

Finally, we construct our paper as follows. The next session describes the materials and methods. We present the research findings and results in the third section. Finally, discussions and concluding remarks are in the fourth section.

2. Methodology

2.1. Theoretical Foundation

2.1.1. Mindsponge theory and granular interaction thinking

MT has been effectively applied in various fields, including education and positive psychology, to explore the psychological mechanisms underlying the relationship between employee proactivity and knowledge sharing (Wang et al., 2024). Additionally, MT has been utilized to advance scholarly community coaching as a pedagogical method grounded in the Serendipity-Mindsponge-3D Knowledge (SM3D) management framework (Jin et al., 2023). This makes MT particularly suitable for explaining the complex connections between knowledge acquisition, dissemination, and teaching motivation among academic staff in Vietnam.

MT originated as a mechanism to explain the dynamics of acculturation and global thinking (Vuong & Napier, 2015). Later, it evolved into a comprehensive theory by incorporating evidence from life and neurosciences (Vuong, 2023). Recently, MT has been refined into a granular interaction thinking theory, with this granular interaction mechanism now being central (Vuong & Nguyen, 2024). By integrating principles from quantum physics (Rovelli, 2016, 2018; Keppens, 2018) and Shannon's information theory (Shannon, 1948), the updated MT introduces an entropy-based notion of value to explain better the complexity of human psychology and behavior shaped by various mental processes (Vuong & Nguyen, 2024a; Davies & Gregersen, 2014).

Specifically, the entropy-based notion of value suggests that as the mind accumulates and processes more information, the likelihood of information loss or forgetting increases due to the rising entropy. Therefore, the mind needs to assign a higher probability of being stored and reused to the information that is more important to the mind. Information is defined by Shannon (1948) as potential alternatives. Values are formed through granular interactions between information within the mind and newly absorbed from the environment. During these interactions, the mind expends energy evaluating, comparing, and synthesizing the information to generate insights. These insights, or values, serve to prolong the mind's existence. In this sense, values can be seen as synthetic units of information emerging from the integration and interaction of diverse informational elements (Vuong and Nguyen, 2024b).

2.1.2. Proposed hypotheses

In the current study, the motivation of academic staff can be understood as a mental construct shaped by their cognitive processes. Self-determination theory (SDT), a leading framework for understanding human motivation and well-being, offers valuable insights for analyzing the motivational drivers behind personality and social behavior. SDT categorizes human motivation into two types: autonomous and controlled. Autonomous motivation refers to actions driven by personal interests and values, reflecting intrinsic motivation, while controlled motivation stems from external or internal pressures, reflecting extrinsic motivation (Ryan & Deci, 2023).

Teaching motivation is particularly important in the education sector, as it directly influences student motivation, educational reform, teaching practices, and the psychological fulfillment and well-being of teachers (Han & Yin, 2016). Broadly, motivation is often perceived as an energy or drive that naturally propels people to take action. The concept of the "Zeitgeist of interest" connects motivational theories to the domain of teaching, shaping the understanding of teaching motivation (Watt & Richardson, 2008). According to SDT, teaching motivation is defined as either a reflection of personal interests and values that inspire individuals to teach or as a response to external or internal pressures that compel them to teach (Ryan & Deci, 2023).

Teaching motivation can arise from a variety of factors. These may include institutional values, such as the opportunity to educate future generations, earn a higher salary, or conduct classroom research. Additionally, motivations not directly tied to institutional benefits, such as the desire to share ideas, empower communities, or enhance one's professional reputation, also play a role (Rao, 2016). The fulfillment of these desires relies heavily on access to sufficient knowledge, which is a critical condition.

Knowledge acquisition involves the process of extracting, structuring, and organizing knowledge from various sources. It refers to the process of absorbing and integrating new knowledge and information, typically through reading, research, training, or experiential learning (Aronson, 2003). This process can be metaphorized as the growth of a "tree of knowledge." Bosancic (2016) introduced the Data-Information-Knowledge-Wisdom (DIKW) pyramid to illustrate the unique role of information in the knowledge acquisition process. In this model, information acts as a "flow" that nourishes the "tree of knowledge," which is rooted in "data earth" and fueled by the "information sap" rising from the roots to the top, illuminated by the "sun of the mind." Information serves as the critical link between the "world of data" and the "world of knowledge." Through the multi-filtering process of the human mind, individuals can selectively retain beneficial information, which contributes to the growth of their "tree of knowledge" (Vuong, 2023; Nguyen et al., 2023).

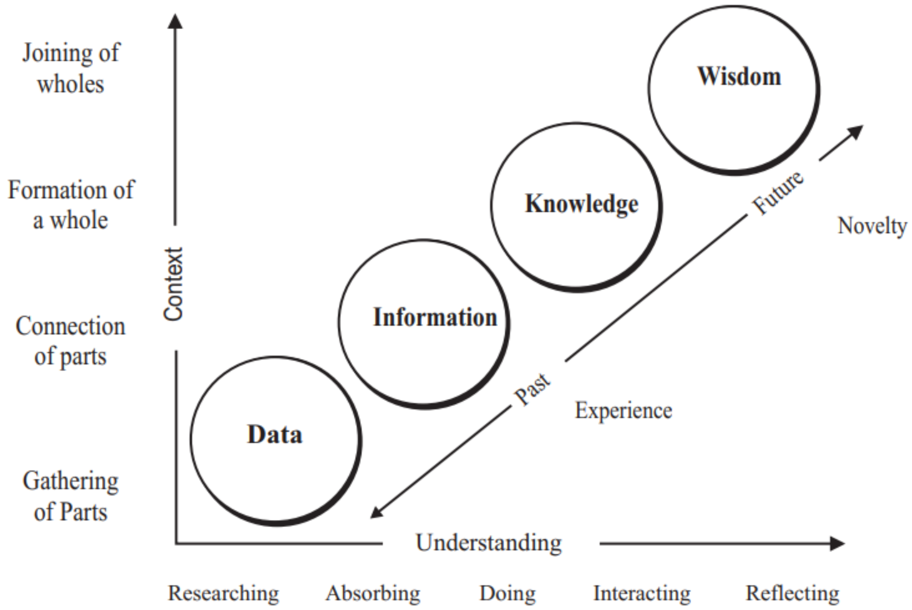

Figure 1. DIKW Model (Source: Senapathi, 2011)

Before knowledge can be used, it must first go through a process of dissemination. Knowledge transfer has historically taken many forms, such as peer discussions on the job, formal apprenticeships, corporate libraries, professional training, and mentoring programs (Senapathi, 2011). In higher education, knowledge dissemination among faculty members is strongly encouraged to foster the growth of the "tree of knowledge" within academic communities. Since highly educated individuals tend to be more discerning in evaluating the value of new information during the dissemination process or information exchange activities, such processes may stimulate further information-seeking and knowledge-exchanging behaviors. These behaviors can lead to clarification, development, or advancement in knowledge utilization. The advent of information and communication technology (ICT) and the internet has further facilitated the instant availability of knowledge, accessible with just a click from anywhere in the world.

For these reasons, knowledge acquisition and dissemination play a crucial role in shaping the professional development of faculty members in higher education institutions. The existing knowledge base—comprising both breadth and depth—interacts with knowledge integration mechanisms such as acquisition and dissemination (Zhou & Li, 2012). In the context of teaching, a growing "tree of knowledge" among faculty members enhances the quality of information transferred to students during classroom instruction. The more knowledge faculty members have, the more they are inclined to share it. Since motivation can be externally driven, knowledge acquisition and dissemination activities within the faculty may provide a supportive environment that fosters and develops teaching motivation. Based on this reasoning, it can be expected that knowledge acquisition and dissemination are positively associated with academic staff's teaching motivation.

However, not all information or knowledge is beneficial. When the volume of information increases without clear prioritization, information entropy also rises substantially, increasing the risk of information loss (Vuong & Nguyen, 2024a; Vuong & Nguyen, 2024b). The more information can be acquired and disseminated within the environment, the more energy the faculty members need to expend in assessing, organizing, and integrating information. In other words, the more energy consumed in filtering and processing information, the more costly the teaching process would become. Consequently, there may be diminishing effects of knowledge absorption and dissemination on teaching motivation as the cognitive costs rise.

2.2. Model Construction

2.2.1. Dataset

The dataset used in this study was generated from 676 academics in Vietnam and was published in *Data in Brief* (Khoa & Huynh, 2023): https://www.sciencedirect.com/science/article/pii/S2352340923005541. This dataset was collected by employing a self-administered questionnaire initially to 700 academics in the five most prominent cities in Vietnam such as Ha Noi, Hai Phong, Da Nang, Ho Chi Minh City, and Can Tho. Applying the purposive sampling, enumerators finally collected 676 responses.

In order to reduce the non-response bias, firstly, the combination of modes of data collection, including online and offline surveys, was used. The questionnaire was distributed directly to the universities via mail for the lecturers, and the online questionnaire was sent via the lecturer's email. Secondly, a monetary incentive through the electronic wallet was adopted to encourage the lecturer's response after they finished the questionnaire. For that reason, a high response rate was obtained (more than 96%).

The self-administered instrument was developed by modifying the original instrument of the knowledge management system from Ngoc-Tan and Gregar (2018) and utilizing the newly developed instrument of teaching motivation based on the studies of Tang et al. (2016) and Wilkesmann and Lauer (2020). The instrument comprised three sections, as explained below:

1. Screening questions assessing the presence of any knowledge management system in the institution, and the last time of access to this system.

2. The main questions assessing the knowledge management system consisting three constructs (knowledge acquisition, knowledge dissemination, and knowledge utilization), academic staff satisfaction, and teaching motivation.
3. Demographic questions assessing the general characteristics of study respondents (gender, age group, major, and education level).

All participants have used the knowledge management system for at least three months. Table 1 below presents the demographic characteristics of study respondents in detail.

Table 1. Demography characteristics

Characteristics	**Frequency (F)**	**Percentage (%)**
Gender:		
1. Male	341	50.4
2. Female	335	49.6
Age group (y.o.):		
1. 24-30	218	32.2
2. 31-35	202	29.9
3. 36-40	104	15.4
4. 41-45	62	9.2
5. More than 45	90	13.3
Major:		
1. Management science	232	34.3
2. Technical science	226	33.4
3. Social science	218	32.2
Education level:		
1. Bachelor	54	8.0
2. Master	394	58.3
3. Doctor/Ph.D.	228	33.7

2.2.2. Variable Selection

In the current study, we extracted four variables from the dataset to be employed in statistical analysis (see Table 2). To measure two constructs of the knowledge management system, we employed variables of *KnowledgeAcquisition* (average value of six items: Cronbach's Alpha = 0.846) and *KnowledgeDissemination* (average value of seven items: Cronbach's Alpha = 0.927), which reflected the agreement level of knowledge acquisition and dissemination, respectively. To measure teaching motivation among academic staff, we employed the variable *TeachingMotivation* (average value of four items: Cronbach's Alpha = 0.877), which reflected the level of teaching motivation among lecturers. Table 1 below explains the variables' description in detail.

Table 2. Variable Description

Variable's Name	Description	Data Type	Value
KnowledgeAcquisition	The agreement level on knowledge acquisition items' assessment	Numerical	1 = Totally disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Totally agree
KnowledgeDissemination	The agreement level on knowledge dissemination items' assessment	Numerical	
TeachingMotivation	The agreement level on teaching motivation items' assessment	Numerical	

2.2.3. Statistical Model

In this study, we examined how knowledge acquisition and dissemination are associated with teaching motivation among academic staff in Vietnam. The parsimonious model is illustrated in Figure 2 below.

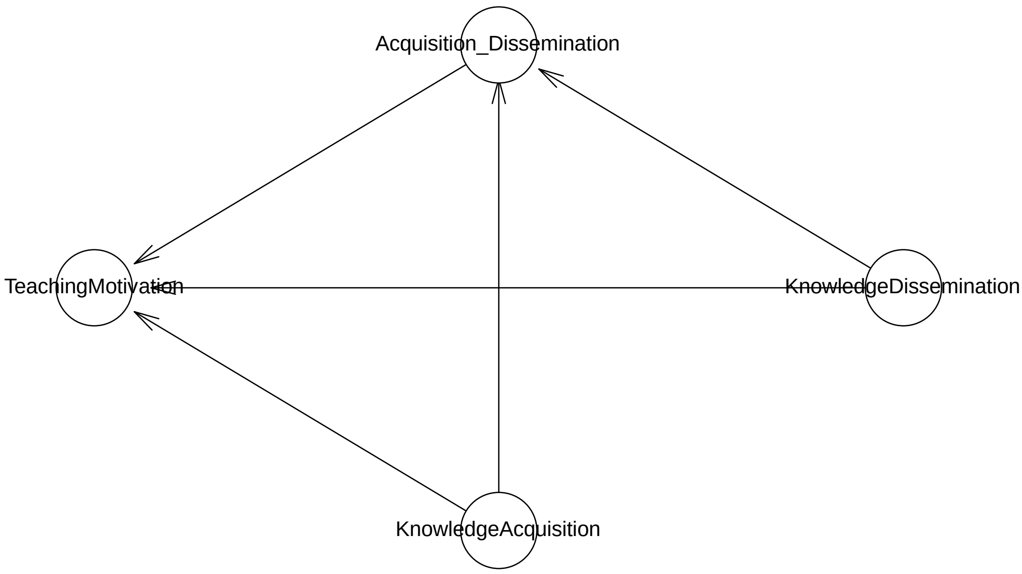

Figure 2. Analytical Model

The formula of this model is described below.

$$TeachingMotivation \sim \text{normal}(\mu, \sigma) \quad (1.1)$$

$$\mu_i = \beta_0 + \beta_1 * KnowledgeAcquisition_i + \beta_2 * KnowledgeDissemination_i + \beta_3 * KnowledgeAcquisition * KnowledgeDissemination_i \quad (1.2)$$

$$\beta \sim normal(M, S) \quad (1.3)$$

The probability around μ is determined by the form of normal distribution, whose width is specified by the standard deviation σ. The teaching motivation of academic staff i is indicated by μ_i . $KnowledgeAcquisition_i$ and $KnowledgeDissemination_i$ are the agreement level of staff i on the applied knowledge management system in their institution. The model has an intercept β_0 and three coefficients, β_1-β_3. The coefficients of the predictor variables are distributed as a normal distribution around the mean denoted M and with the standard deviation denoted S.

2.3. Data Analysis and Validation

Bayesian Mindsponge Framework (BMF) analytics was employed in the current study for several reasons (Nguyen, La, & Le, 2022; Vuong, Nguyen, & La, 2022). First, the analytical method integrates the logical reasoning capabilities of MT with the inferential advantages of Bayesian analysis, exhibiting a high degree of compatibility (Nguyen, La, & Le, 2022). Second, Bayesian inference is a statistical approach that treats all the properties (including the known and unknown ones) probabilistically (Csilléry et al., 2010;

Gill, 2015), enabling reliable prediction of parsimonious models. Nevertheless, utilizing the Markov chain Monte Carlo (MCMC) technique still allows Bayesian analysis to deal effectively with various intricate models, such as multilevel and nonlinear regression frameworks (Dunson, 2001). Third, Bayesian inference has various advantages over the frequentist approach. One notable advantage is the ability to utilize credible intervals for result interpretation instead of relying solely on the dichotomous decision based on *p*-values (Halsey et al., 2015; Wagenmakers et al., 2018). The Bayesian analysis was performed on R using the **bayesvl** open-access package, which provides good visualization capabilities (La & Vuong, 2019).

In Bayesian analysis, selecting the appropriate prior is required during the model construction process. Due to the exploratory nature of this study, uninformative priors or a flat prior distribution were used to provide as little prior information as possible for model estimation (Diaconis & Ylvisaker, 1985). The Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics were employed to check the models' goodness of fit (Vehtari & Gabry, 2019; Vehtari, Gelman, & Gabry, 2017). LOO is computed as follows:

$$LOO = -2LPPD_{loo} = -2\sum_{i=1}^{n} \log \int p(y_i|\theta)p_{post(-i)}(\theta)d\theta$$

$p_{post(-i)}(\theta)$ is the posterior distribution calculated through the data minus data point i. The *k*-Pareto values are used in the PSIS method for computing the LOO cross-validation in the R **loo** package. Observations with *k*-Pareto values greater than 0.7 are often considered influential and problematic for accurately estimating LOO cross-validation. When a model's *k* values are less than 0.5, it is typically regarded as being fit.

If the model fits well with the data, we will proceed with the convergence diagnoses and results interpretation. In the current study, we validated the convergence of Markov chains using statistical values and visual illustrations. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) can be used to assess the convergence. The *n_eff* value represents the number of iterative samples that are not auto-correlated during stochastic simulation, while the *Rhat* value is referred to as the potential scale reduction factor (Brooks & Gelman, 1998). If *n_eff* is larger than 1000, it is generally considered that the Markov chains are convergent, and the effective samples are sufficient for reliable inference (McElreath, 2018). As for the *Rhat* value, if the value exceeds 1.1, the model does not converge. The model is considered convergent if *Rhat* = 1. Visually, the Markov chains' convergence was also validated using trace plots, Gelman–Rubin–Brooks plots, and autocorrelation plots.

Data and code snippets of this initial analysis were deposited on a preprint server to address data transparency, enabling public evaluation and reproducibility (Vuong, 2018): https://zenodo.org/records/11213426.

3. Results

3.1. Model 1

Before interpreting the results, evaluating the goodness of fit for Model 1 with the data is crucial. As shown in Figure 3, all estimated *k*-values fall below the 0.5 threshold, indicating a good fit between the model and the data.

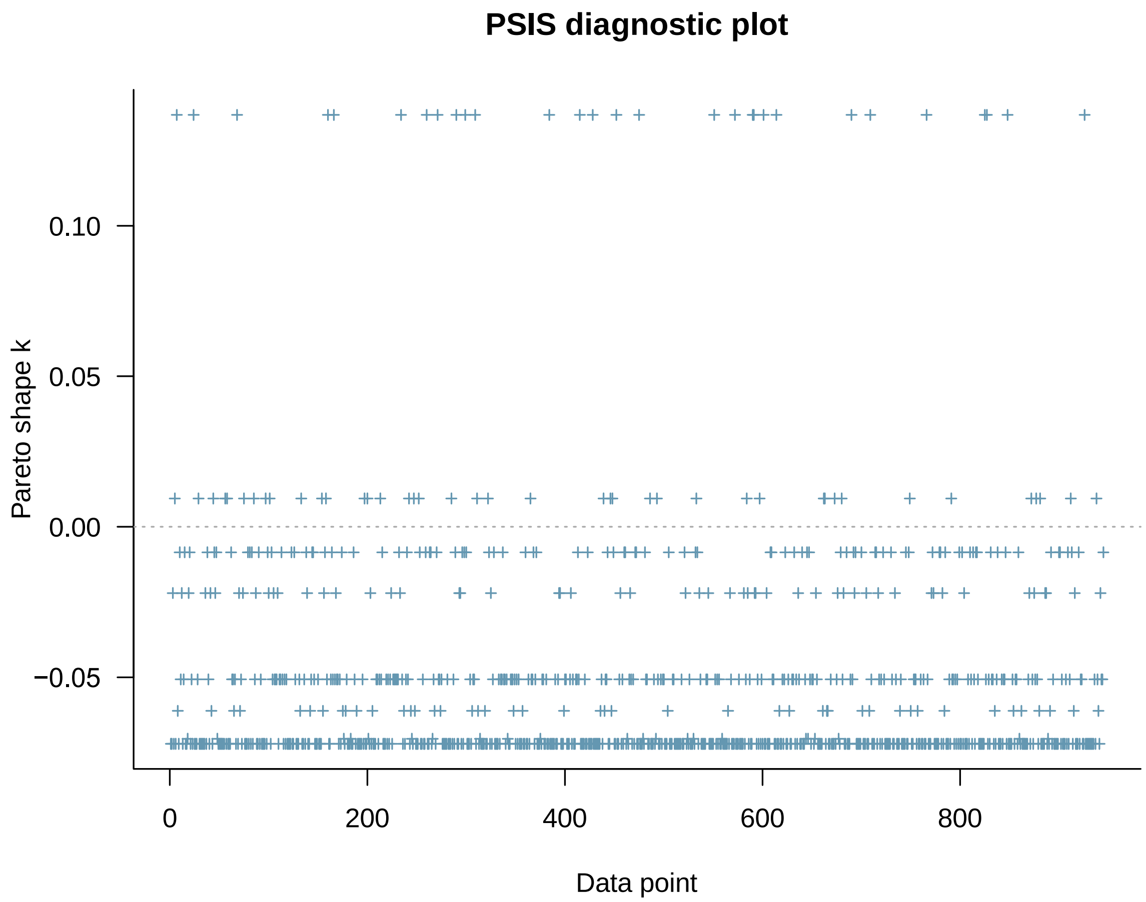

Figure 3. Model 1's PSIS-LOO diagnosis

The statistical information regarding the posterior distributions of Model 1 appears in Table 3. All *n_eff* values are above 1000, and *Rhat* values equal 1. This indicates that the Markov chains for Model 1 have converged successfully. Further evidence of this convergence is visible in the trace plots depicted in Figure 4, where all chain values stabilize around a central equilibrium after the 2000th iteration.

Table 3: Estimated results of Model 1

Parameters	Mean	SD	*n_eff*	*Rhat*
Constant	-1.14	0.38	2636	1
KnowledgeAcquisition	0.88	0.11	2771	1
KnowledgeDissemination	0.93	0.12	2736	1
*KnowledgeAcquisition**	-0.13	0.03	2619	1

KnowledgeDissemination				

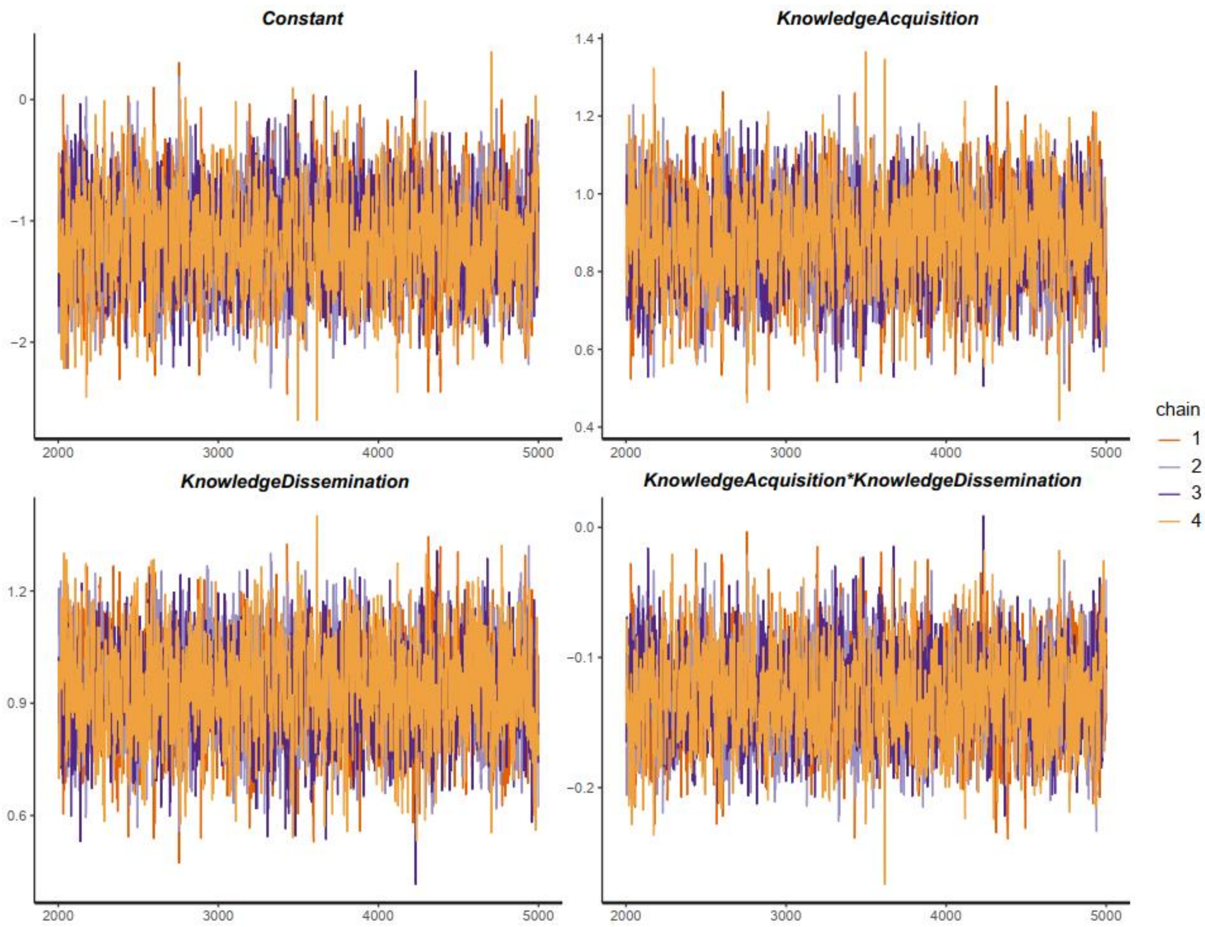

Figure 4. Model 1's trace plots

The Gelman-Rubin-Brooks plots, along with the autocorrelation plots, confirm the effective convergence of the Markov chains. In the Gelman-Rubin-Brooks plots, the *y*-axis illustrates the shrink factor (or Gelman-Rubin factor), while the *x*-axis shows the simulation's iteration sequence. In Figure 5, all parameters' shrink factors quickly approach 1 before the 2000th iteration (during the warm-up phase). This finding indicates a lack of divergence among the Markov chains.

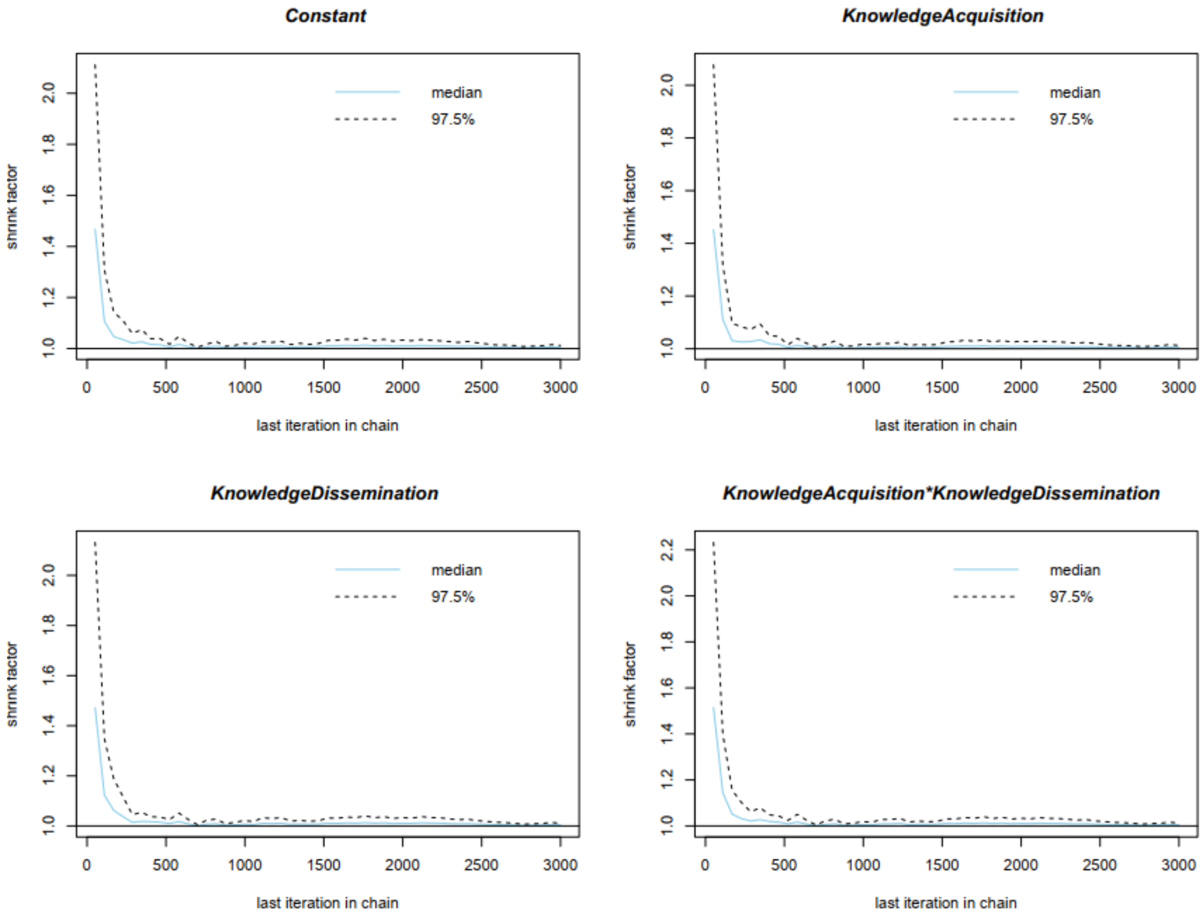

Figure 5. Model 1’s Gelman-Rubin-Brooks plots

The Markov property refers to the memorylessness of a stochastic process, meaning that future values are independent of past values and depend only on the present state. To assess this, researchers use autocorrelation plots to analyze the degree of autocorrelation within iterations of the process. The graphs in Figure 6 illustrate the average autocorrelation for each Markov chain on the vertical axis, with the lag represented on the horizontal axis. Visually, all Markov chains exhibit a rapid decline in autocorrelation, approaching zero after only a few lags (specifically before lag 5), indicating that the chains adhere to the Markov property and converge appropriately.

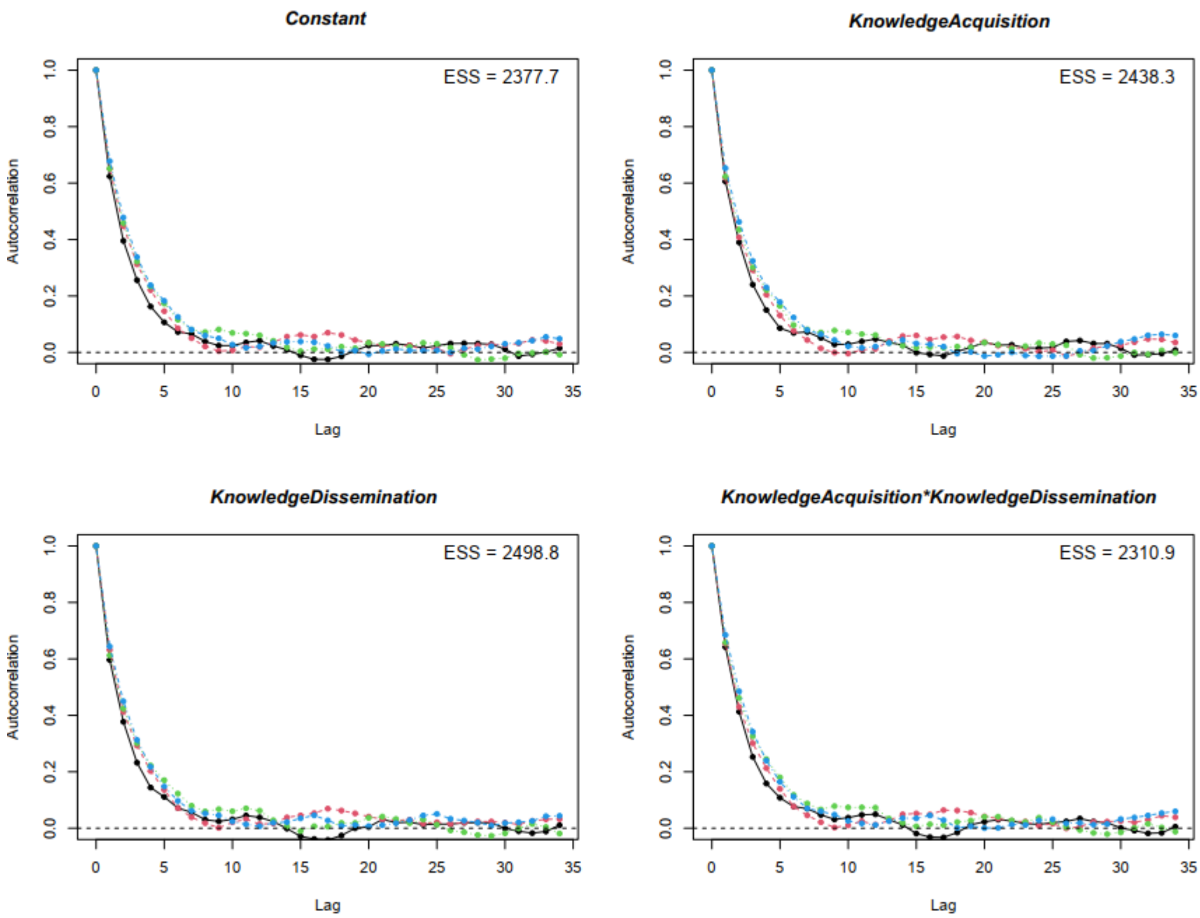

Figure 6. Model 1's autocorrelation plots

Since all the diagnostics confirm the convergence of Markov chains, the simulated results are eligible for interpretation. The estimated results of Model 1 show that knowledge acquisition and dissemination are positively associated with academic staff's teaching motivation ($M_{KnowledgeAcquisition}$ = 0.88 and $S_{KnowledgeAcquisition}$ = 0.11; $M_{KnowledgeDissemination}$ = 0.93 and $S_{KnowledgeDissemination}$ = 0.12). However, the interaction between $KnowledgeAcquisition$ and $KnowledgeDissemination$ shows a negative association with $TeachingMotivation$ ($M_{KnowledgeAcquisition*KnowledgeDissemination}$ = -0.13 and $S_{KnowledgeAcquisition*KnowledgeDissemination}$ = 0.03). The posterior estimations of the coefficients are illustrated in Figure 7. The posterior distributions of $KnowledgeAcquisition$ and $KnowledgeDissemination$ are located entirely on the positive side, while the posterior distribution of $KnowledgeAcquisition * KnowledgeDissemination$ lies entirely on the negative side. These distributions indicate high reliability of their associations with $TeachingMotivation$.

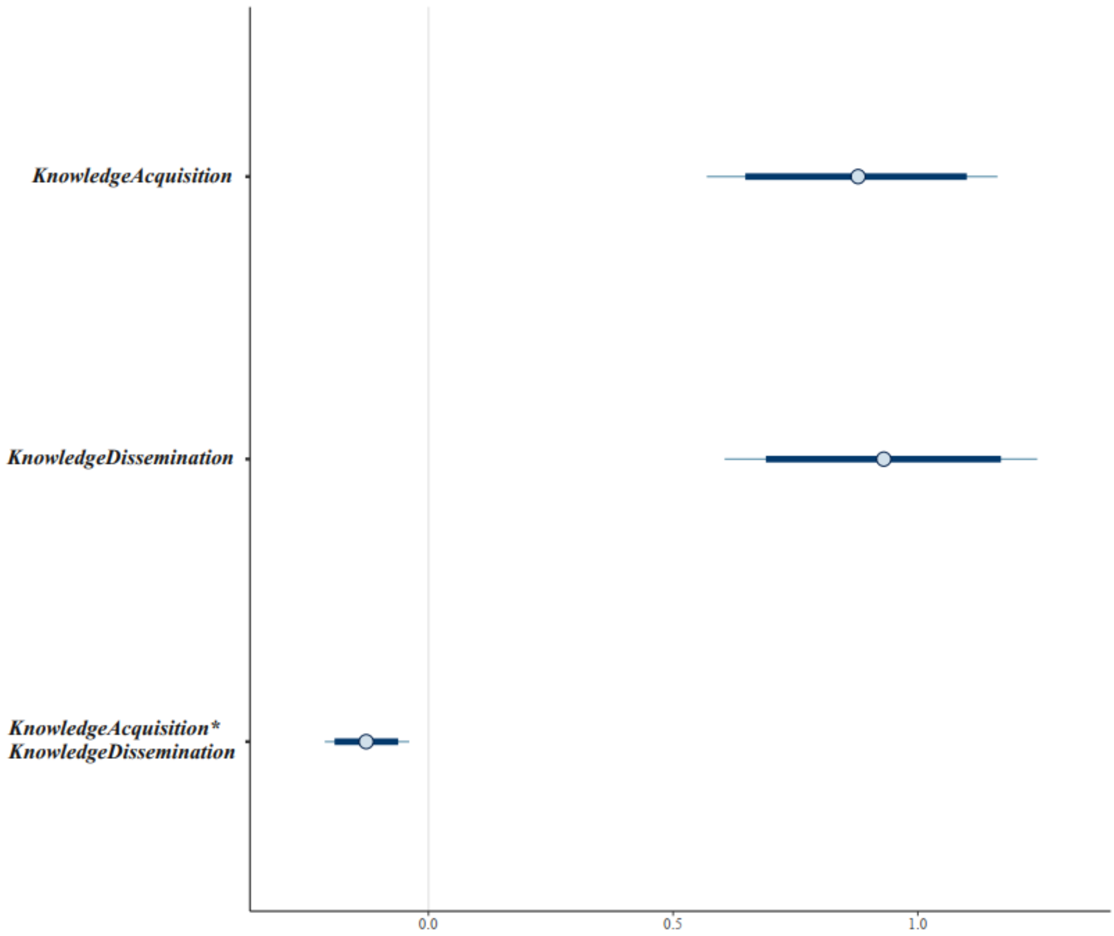

Figure 7. Model 1's posterior distributions

For clarity, we applied the coefficients' mean value to Equation 1.2 to calculate the degree of teaching motivation according to the academic staff's perceived level of knowledge acquisition and dissemination within the institution. The estimated teaching motivation is visualized in Figure 8. As can be seen from Figure 8, the teaching motivation level generally increases as the levels of knowledge acquisition and dissemination increase. However, the increasing margin of teaching motivation declines as both the levels of knowledge acquisition and dissemination increase. These results validate our presumptions that while $KnowledgeAcquisition$ and $KnowledgeDissemination$ are positively associated with $TeachingMotivation$, there would be a diminishing effect on $TeachingMotivation$ when both $KnowledgeAcquisition$ and $KnowledgeDissemination$ rise higher.

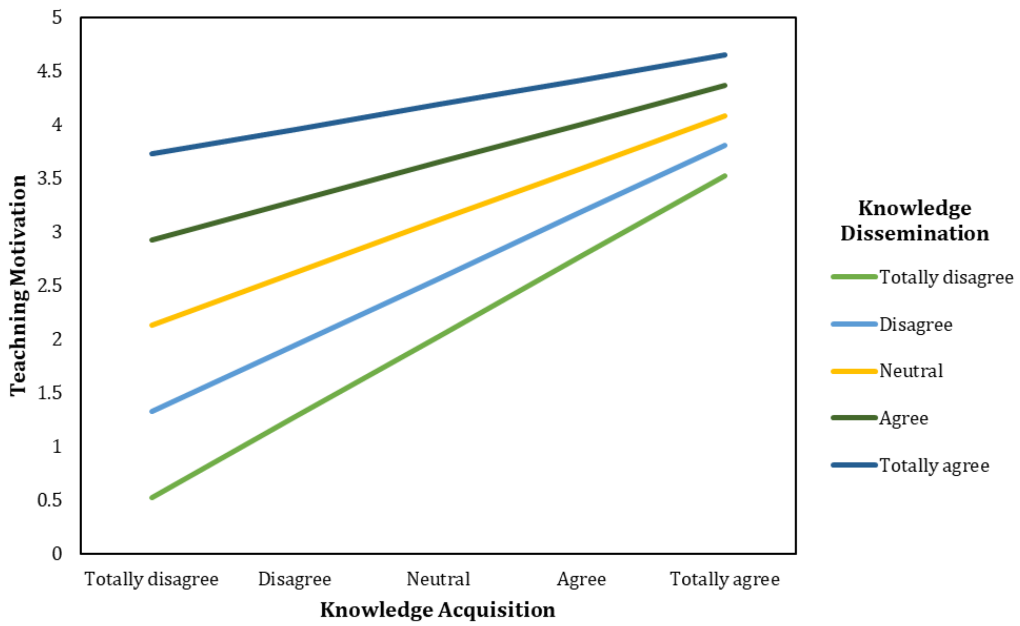

Figure 8: Estimated teaching motivation according to the level of knowledge acquisition and dissemination

4. Discussion

The study utilized Bayesian Mindsponge Framework analytics to investigate the complex interplay between knowledge acquisition, knowledge dissemination, and academic staff's teaching motivation. An analysis of data from 676 academic staff at Vietnamese higher education institutions revealed positive associations between knowledge acquisition, knowledge dissemination, and teaching motivation. However, the interaction between knowledge dissemination and acquisition was found to have a negative association with teaching motivation.

The overall findings of the study align with the preliminary hypotheses, grounded in the Mindspong theory framework. Specifically, knowledge acquisition and dissemination demonstrate positive associations with teaching motivation among academic staff. This supports Duong et al. (2022) assertion that effective knowledge management—encompassing acquisition, dissemination, and utilization—enhances employee motivation and fosters enjoyment in professional roles within Vietnamese public universities. As individuals acquire additional knowledge or pursue further education, which bolsters knowledge acquisition, it cultivates a supportive work environment, increases internal fulfillment, and elevates their standing within organizations, thereby strengthening their motivation to adopt new practices (Nguyen, 2023; Wang et al., 2019; Williams et al., 2015). Additionally, effective internal communication enhances employee morale, attitudes, and behaviors (Ndlovu et al., 2021). By applying these robust mechanisms, individuals become more engaged with their organization (Tkalac Verčič et al., 2012), with prior engagement serving as a foundation for increased motivation and improved performance (Martin et al., 2017).

When considering the combined effect of knowledge acquisition and dissemination on teaching motivation, we found that the interaction between these two elements is negatively correlated with teaching motivation. The result can be explained by the potential emergence of a resource curse within academies and institutions: an excess of knowledge without the sufficient ability to leverage it. As explained above by the mindsponge theory, the more knowledge available within the institution, the more energy and time the academic staff will need to spend evaluating, organizing, and integrating it. Given that the energy and time of each academic staff is limited (Vuong & Nguyen, 2024a), the amount of knowledge surpassing the capability that the staff can process could lead to declining efficiency of utilizing the knowledge. Earlier studies conducted by Arif and Rahman (2018) and Ngoc-Tan and Gregar (2018) posited that knowledge utilization, rather than knowledge acquisition and knowledge dissemination, positively influences administrative innovation in universities in Vietnam. When the improvement in knowledge acquisition and dissemination could not only improve the working efficiency (i.e., preparing teaching materials) but also require more energy and time to process, it could result in a diminishing effect of knowledge acquisition and dissemination on teaching motivation.

These findings have important implications for improving the effectiveness of knowledge management systems, particularly in knowledge acquisition and dissemination, to enhance academic staff's teaching motivation. It is crucial for government bodies and technology developers to continue investing in infrastructure, server frameworks, and data storage solutions that support effective knowledge resource management while ensuring regular updates for prompt knowledge sharing (Duong et al., 2022). Technology providers should aim to create intuitive digital tools that offer a seamless user experience for academic staff, thereby encouraging widespread use of knowledge management systems. Institutions, meanwhile, should leverage digital resource platforms to archive and distribute knowledge assets effectively, as well as facilitate virtual conferences and workshops to promote knowledge dissemination among faculty members (Duong et al., 2022). To increase the staff's capability to process these systems, it is recommended that the knowledge systems are refined to reduce complexity and that staff are trained with better knowledge processing methods. Doing so can help institutions mitigate the risks of a resource curse caused by knowledge overload. Finally, implementing strong policies focused on knowledge quality—including educational materials, learner resources, and research outputs—and ensuring equitable and efficient access to knowledge can significantly improve knowledge storage and sharing, thereby enhancing teaching motivation.

The present study encounters several limitations, which we have outlined here for transparency (Vuong, 2020). First, the dataset comprises only samples from Vietnam, which may not fully represent countries and regions with different knowledge management systems. Therefore, caution is advised when generalizing the results to other international contexts. Future research should aim to test the information processing hypothesis associated with the mindsponge theory across a broader range of regions and settings. Another limitation is the reliance on survey data, which may not fully capture the dynamic interactions between knowledge management systems and academic staff's teaching motivation. Experimental approaches could be employed in future research to address these gaps.

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