Cloud-Based E-Learning in Higher Education: Determinants of Adoption and PSO-Based Optimization of Secure File Processing

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Abstract

Cloud computing can provide higher education institutions (HEIs) with scalable e-learning infrastructure without large capital investment, yet adoption in developing regions remains limited by security, organisational, technical and external concerns, and cloud-hosted e-learning services must process large volumes of learner files efficiently. The present study addresses both the adoption and the service-delivery sides of this problem. First, a research model comprising 42 factors grouped into four perspectives—security, organisational challenge, technical and external pressure—was evaluated through a questionnaire survey of 960 respondents from HEIs and technical colleges in North India. The measurement model showed Cronbach's α of 0.92–0.95, composite reliability of 0.93–0.95 and average variance extracted of 0.67–0.82. Endorsement of individual factors ranged from 68.4% to 81.8%, and all factor-level regressions were significant ($p < 0.001$), with the strongest standardised coefficients for integrity maintenance ($\beta = 0.967$), cost reduction (0.945), technological infrastructure (0.943) and encryption (0.917); the security perspective showed the highest mean coefficient (0.788). Second, motivated by these security and resource concerns, an e-learning framework in which files are protected with RSA encryption and allocated to virtual machines by particle swarm optimisation (PSO) was simulated. For file sizes of 10–100 MB, the proposed PSO allocation reduced processing time by 12.4–23.2% relative to an existing PSO scheme (18.7% in aggregate), and increasing the number of servers from one to four reduced processing time by 45.5–59.5%. The findings provide evidence-based priorities for institutional cloud adoption together with a practical allocation strategy for cloud-hosted e-learning.

Keywords: *Cloud computing; e-learning; higher education; technology adoption; PLS; particle swarm optimisation; RSA encryption; virtual machine allocation*

1. INTRODUCTION

Information and communication technologies have changed how higher education is delivered. Digital textbooks, recorded lectures, online assessments and collaborative tools increasingly complement or replace printed material and classroom-only instruction, and computer-based and adaptive testing are now feasible at institutional scale. Delivering such services, however, requires substantial computing, storage and network resources, together with skilled staff to operate and maintain them. Many institutions—particularly in developing regions—cannot afford to procure and maintain this infrastructure individually, and the resulting disparities limit access to high-quality e-learning.

These constraints are particularly acute in large and diverse higher-education systems such as India's, where well-resourced universities coexist with technical colleges and institutions that serve economically disadvantaged learners. For such institutions, maintaining dedicated servers, licensed software and specialised support staff for every course is often impractical, and learners without access to adequate personal computing resources are at a further disadvantage. Shared, centrally managed infrastructure that institutions can access on demand could narrow this gap by giving learners of less-resourced institutions access to the same digital resources and services as those of better-funded ones.

Cloud computing offers an alternative. Defined by NIST as a model for ubiquitous, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned with minimal management effort [1], it allows institutions to consume software, platforms and infrastructure as services and to pay only for what they use [2], [3]. For education, this means that learning management systems, virtual laboratories and digital libraries can be hosted centrally and accessed from any location and device [4], [5], [6]. A cloud-based e-learning system, illustrated in Fig. 1,

typically comprises a user layer, in which learners and staff of different institutions submit requests, and a datacenter layer, in which virtualised servers host the e-learning services and databases.

Despite these advantages, the decision to migrate educational services to the cloud is not purely technical. Studies in several countries have shown that adoption depends on a combination of security and privacy concerns, organisational readiness, technical characteristics of the services and external pressures [7], [8], [9], [10]. Moving learning resources to a third-party provider creates a dependence on that provider and on network connectivity: if the provider discontinues its service or connectivity is inadequate, data and services may become unavailable [11], [12]. Once a cloud-based system is adopted, a second, operational problem arises. The datacenter must serve a continuous stream of file requests from many learners, with files of different sizes and computational demands, on servers of heterogeneous capacity. Allocating these requests inefficiently increases processing time and degrades the user experience, while security requirements add encryption overhead to every transaction.

These two problems are interdependent. Institutional decision-makers are more likely to adopt cloud-based e-learning if the concerns that matter most to their stakeholders are demonstrably addressed, and system designers can prioritise features more effectively if they know which concerns carry the greatest weight. An evidence base that connects the determinants of adoption with the design and evaluation of the underlying service mechanisms is therefore of practical value to both groups.

2. LITERATURE REVIEW

2.1 Cloud computing in education

The educational potential of cloud computing was recognised early. Sultan [4] examined whether cloud computing represented "a new dawn" for education, and Ercan [5] discussed its effective use in educational institutions, emphasising reduced infrastructure costs and ubiquitous access to applications and data. Armbrust *et al.* [2] articulated the economic and technical characteristics that make cloud services attractive—elasticity, pay-per-use pricing and the absence of up-front investment—and the NIST definition [1] formalised the service (SaaS, PaaS, IaaS) and deployment (private, community, public, hybrid) models. Practical deployments include the virtual computing laboratory of North Carolina State University, which provided on-demand computing environments to students and faculty [6], and the concept of education and learning as a service (ELaaS) [17]. Truong *et al.* [18] examined cloud computing for education and research in developing countries, where the cost and scalability advantages are particularly relevant, and González-Martínez *et al.* [19] provided a state-of-the-art survey of the field. The authors' earlier work has also reported observations on cloud computing in education [20].

2.2 Determinants of cloud computing adoption

Adoption of cloud computing has been studied extensively in organisational settings. Lin and Chen [21] analysed cloud computing as an innovation from the perspective of perception, attitude and adoption, Gupta *et al.* [22] examined usage and adoption by small and medium businesses, and Hassan [23] investigated organisational factors affecting adoption by service-sector SMEs. In Saudi Arabia, Alhammadi *et al.* [24] identified determinants of adoption and Al-Ruithe *et al.* [25] assessed the current state of adoption in public-sector organisations, while Alanezi [26] conducted a qualitative evaluation in private and public organisations, in which privacy, government policy, lack of education and loss of control emerged as inhibitors and cost reduction, improved IT performance, scalability and flexibility as drivers.

Studies specific to higher education show a similar multi-dimensional picture. Tashkandi and Al-Jabri [7] carried out an exploratory study of adoption by HEIs in Saudi Arabia. Sultana *et al.* [8] examined seventeen candidate factors at the University of Dhaka and, through multiple regression, identified service availability, cloud control ability, resource need, lack of infrastructure, usefulness in education and lack of staff training as the main factors. Tariq *et al.* [9] studied HEIs in Punjab, Pakistan, using a model with five perspectives—security, organisational challenges, technical issues, external pressure and advantages—and 34 hypotheses tested by t-tests and regression. Klug and Bai [10] analysed factors affecting adoption among universities and colleges in the United States and Canada, Sabi *et al.* [13] conceptualised a model for adoption in education that incorporates contextual, economic and technological influences, and Karim and Rampersad [27] addressed cloud computing in education in developing countries. Collectively, these studies establish

security, organisational, technical and environmental factors as the principal dimensions of adoption, but the factor sets, contexts and analytical methods vary widely, and Indian HEIs and technical colleges are under-represented.

2.3 Security and resource management in educational clouds

Security is consistently reported as a primary concern. Popović and Hocenski [11] reviewed the security issues and challenges of cloud computing, and Dong *et al.* [12] addressed security and privacy for storage and computation in the cloud. Public-key cryptography, notably the RSA algorithm [31], is widely used to protect data exchanged between clients and cloud services because it avoids the secure distribution of a shared secret key. On the resource-management side, the allocation of workloads to virtual machines is a combinatorial optimisation problem for which metaheuristics are frequently employed: Gao *et al.* [14] proposed a multi-objective ant colony system for virtual machine placement, Liu *et al.* [15] an energy-aware ant colony approach, and Joseph *et al.* [16] a family genetic algorithm for virtual machine allocation. Particle swarm optimisation [32], which models the collective search of a swarm guided by individual and global best positions, is attractive for such problems because of its few control parameters and fast convergence; metaheuristic approaches for virtualised data and task execution in the cloud have also been examined in the authors' earlier work [33], [34].

Two observations follow from this body of work. First, the metaheuristics applied to cloud resource management are usually evaluated on generic workloads and objectives such as energy consumption or the number of active hosts; the processing time experienced by users of a specific application domain, such as learners submitting files of varying size, is less often the explicit objective. Second, the security mechanisms and the allocation mechanisms are commonly studied in isolation, although in an operational e-learning service every request passes through both. Evaluating allocation strategies within a framework that also incorporates encryption is therefore closer to the conditions of a practical deployment.

2.4 Research gap

The literature thus provides two largely separate bodies of work: stakeholder studies that identify which concerns influence the adoption of cloud computing in education, and technical studies that optimise resource allocation or strengthen security in generic cloud environments. The present study links the two by evaluating a comprehensive adoption model in the Indian higher-education context and by quantitatively assessing a secure, PSO-based file-processing scheme that responds to the security and resource concerns revealed by the survey.

3. MATERIALS AND METHODOLOGY

3.1 Research model and hypotheses

The research model, shown in Fig. 1, relates 42 candidate factors to the adoption of cloud computing in HEIs and technical colleges. The factors were derived from the literature and from discussions with academic staff and cloud practitioners, and they were grouped into four perspectives: security (8 factors, e.g. security effectiveness, unauthorised access, encryption, integrity maintenance), organisational challenge (12 factors, e.g. insufficient staff, cost of IT operation, training for staff, energy efficiency), technical (15 factors, e.g. quality of service, compatibility, service availability, dependence on the service provider, technological infrastructure) and external pressure (7 factors, e.g. government pressure, peer pressure, awareness, cost of access, cost reduction). For each factor a hypothesis H1–H42 was formulated stating the expected direction of its influence on adoption; for example, security effectiveness and data security were hypothesised to influence adoption positively, whereas unauthorised access, insufficient skilled staff and dependence on the service provider were hypothesised to influence it negatively.

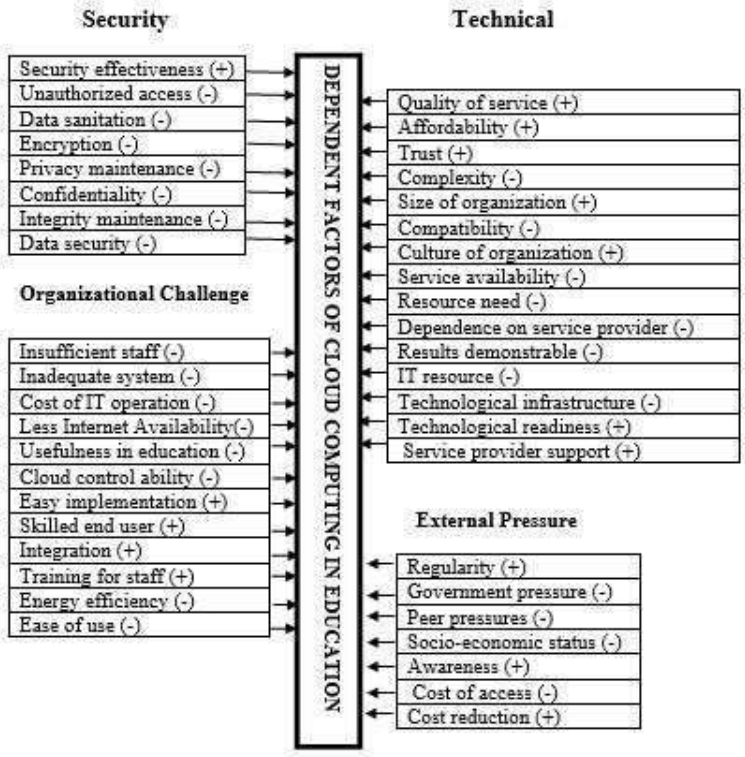


Fig. 1. Research model for the evaluation of cloud computing adoption in education: 42 factors grouped into security, organisational-challenge, technical and external-pressure perspectives, with the hypothesised direction of influence (+/−).

3.2 Survey design, sampling and analysis

A structured questionnaire was developed to cover all factors of the model. It combined short-answer and multiple-choice items, closed yes/no (Y/N) items asking respondents whether they regarded each factor as significant for adoption, and Likert-type items measuring the perceived importance of the factors. The questionnaire was administered in paper form and through online (Google Forms) surveys to students and staff of HEIs and technical colleges in North India who study or work in computer science. Respondents were aged between 17 and 49 years and comprised administrative staff, faculty members, and postgraduate and undergraduate students. Non-probability convenience sampling was used. Approximately 1,100 responses were collected, of which 960 complete and valid responses were retained for analysis, a usable response rate of about 87%.

The data were analysed with IBM SPSS and SmartPLS. Descriptive statistics, including the proportion of respondents endorsing each factor, were computed first. The reliability and validity of the four latent constructs were then assessed with a partial least squares (PLS) measurement model [28], [29], using Cronbach's α, composite reliability (CR) and average variance extracted (AVE) with the commonly adopted thresholds $\alpha > 0.7$, $CR > 0.7$ and $AVE > 0.5$ [30]. Finally, each hypothesis was tested by regressing adoption on the corresponding factor and evaluating the standardised coefficient β, the t-statistic and its significance. The endorsement proportion for factor k is

$$E_k = (Y_k / N) \times 100\%, \qquad N = 960 \tag{1}$$

where Y_k is the number of respondents answering "yes" for factor k. The proportion E_k measures how widely a factor is recognised as relevant, whereas β measures how strongly variation in the factor is associated with adoption; the two indicators therefore capture different aspects of importance.

3.3 Secure cloud-based e-learning framework

Within the e-learning architecture of Fig. 1, learners from different institutions submit file requests to a request queue in the user layer, and the datacenter layer allocates each request to one of the virtual machines (VMs) into which the physical servers are partitioned by virtualisation. To address the security concerns that the survey places among the most

influential factors, files exchanged between clients and the cloud are protected by RSA public-key encryption [31], whose steps are shown in Fig. 3. Two large primes p and q are selected and the public and private keys are derived as

$$n = p \cdot q, \quad \varphi(n) = (p-1)(q-1)$$
$$1 < e < \varphi(n), \ \gcd(e, \varphi(n)) = 1, \quad e \cdot d \equiv 1 \ (\mathrm{mod}\ \varphi(n)) \qquad (2)$$

The public key (e, n) is distributed, while the private key (d, n) is kept secret. A plaintext block M ($0 \le M < n$) is encrypted and decrypted as

$$C = M^e \bmod n, \quad M = C^d \bmod n \qquad (3)$$

Because only the public key needs to be shared, key distribution is simpler than for symmetric schemes: a network of n users requires $2n$ keys, compared with $n(n-1)/2$ keys for pairwise symmetric encryption. Decryption verifies that the recovered message equals the original before the data are declared secure

3.4 Problem formulation and PSO-based file allocation

Let I files be allocated to J heterogeneous VMs. The processing time of file i on VM j depends on the computational requirement of the file and on the processing speed of the machine:

$$FP_{ij} = C_i / PS_j \qquad (4)$$

where C_i is the computational requirement (length) of file i and PS_j the processing speed of VM j in million instructions per second (MIPS). The objective is to find the allocation of files to VMs that minimises the file processing time, min FP_{ij}. This allocation problem is solved with PSO [32]. In the adopted mapping, each particle represents a candidate VM assignment, the movement of a file between available processors corresponds to the particle velocity, and the VM currently holding a file corresponds to its position. Each particle i keeps its personal best position $pbest_i$, and the swarm keeps the global best position gbest. At iteration k, the velocity and position are updated as

$$v_i^{k+1} = \omega \cdot v_i^k + c_1 \cdot r_1 \cdot (pbest_i - x_i^k) + c_2 \cdot r_2 \cdot (gbest - x_i^k)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (5)$$

where ω is the inertia weight, c_1 and c_2 are the acceleration coefficients and r_1, r_2 are random numbers in [0, 1] . The algorithm proceeds as follows: (1) initialise the position and velocity of each particle; (2) let each file search for the most suitable processor; (3) evaluate the fitness of each machine from the processing time of Eq. (4); (4) update each particle's personal best if its current fitness is better; (5) select the global best among all machines; (6) update velocities and positions with Eq. (5); (7) repeat steps 2–6 until the maximum number of iterations is reached or the fitness no longer changes over successive iterations; and (8) return the VM that minimises the processing time for the file request.

3.5 Simulation setup

The proposed PSO-based allocation was compared with an existing PSO-based allocation scheme in a simulated datacenter. File requests of 10–100 MB with lengths of 1,000–6,000 were allocated to heterogeneous VMs running on servers of a single datacenter. Two experiments were conducted: (i) processing time versus file size with one server, for the proposed and the existing method, and (ii) processing time versus file size for one to four servers with the proposed method. The simulation parameters are listed in Table 1.

Table 1. Simulation parameters of the file-processing experiments.

Category	Parameter	Value
Files	File size	10–100 MB
	File length	1,000–6,000
VMs and servers	Number of servers	1–4
	VM processing speed	250–300 MIPS
	Memory	256–512
	CPUs	1–5
	Bandwidth	1,000

Category	Parameter	Value
	Virtual machine monitor	Xen
PSO	Number of particles	30
	Maximum iterations	100
	Acceleration coefficients c_1, c_2	2
	Random numbers r_1, r_2	[0, 1]
	Inertia weight ω	0.73

Performance was measured by the file processing time in seconds. The relative reduction in processing time achieved by a configuration A over a reference configuration B, and the speed-up obtained by using *m* servers instead of one, were computed as

$$R_{A/B} = (T_B - T_A) / T_B \times 100\%, \qquad S_m = T_1 / T_m \tag{6}$$

where T denotes processing time. The parallel efficiency S_m/m was additionally used to assess how effectively additional servers are exploited.

4. RESULTS AND DISCUSSION

4.1 Reliability and validity of the measurement model

Table 2 reports the reliability and validity of the four latent constructs. Cronbach's α ranged from 0.9225 (technical) to 0.9549 (external pressure), composite reliability from 0.9281 (organisational challenge) to 0.9483 (external pressure), and AVE from 0.6652 (organisational challenge) to 0.8183 (external pressure). All values exceed the thresholds of 0.7 for α and CR and 0.5 for AVE [30], indicating high internal consistency and adequate convergent validity. The external-pressure construct showed the highest values of all three indicators, suggesting that its items—government and peer pressure, awareness and cost-related items—were perceived most coherently by respondents. The organisational-challenge construct, which groups the most heterogeneous set of twelve factors (staffing, cost, connectivity, usability and energy), had the lowest AVE (0.6652); even so, its items share two-thirds of their variance with the construct, well above the 0.5 threshold.

Table 2. Reliability and validity of the latent constructs.

Construct	Cronbach's α	Composite reliability	AVE
Security	0.9478	0.9481	0.7192
Organisational challenge	0.9324	0.9281	0.6652
Technical	0.9225	0.9377	0.6769
External pressure	**0.9549**	**0.9483**	**0.8183**

4.2 Endorsement and strength of association of individual factors

Table 3 lists, for every factor, the number of respondents who regarded it as significant for adoption, the resulting endorsement proportion (Eq. (1)) and the standardised regression coefficient and t-statistic. All regressions were significant at $p < 0.001$, so every factor of the model is statistically associated with adoption in the surveyed population. Endorsement proportions lay within a relatively narrow band, from 68.44% (integrity maintenance) to 81.77% (data sanitation), with a mean of 74.67% across all items: roughly three out of four respondents considered each factor relevant. The most widely endorsed factors were data sanitation (81.77%), cost of IT operation (80.31%), security effectiveness (79.90%), energy efficiency and regularity (79.17% each), and dependence on the service provider (78.65%).

Table 3. Factor-level results: Y/N responses (N = 960), endorsement E (%), standardised regression coefficient β and t-statistic. All coefficients are significant at $p < 0.001$. Sec. = security; Org. = organisational challenge; Tech. = technical; Ext. = external pressure.

Factor	Persp.	Y/N	E (%)	β	t
Security effectiveness	Sec.	767/193	79.90	0.783	75.432
Unauthorized access	Sec.	696/264	72.50	0.896	117.075
Data sanitation	Sec.	785/175	81.77	0.623	25.457
Encryption	Sec.	734/226	76.46	0.917	85.456
Privacy maintenance	Sec.	676/284	70.42	0.867	53.357
Confidentiality	Sec.	706/254	73.54	0.758	29.569
Integrity maintenance	Sec.	657/303	68.44	0.967	119.045
Data security	Sec.	721/239	75.10	0.496	22.845
Insufficient staff	Org.	735/225	76.56	0.754	31.561
Inadequate system	Org.	698/262	72.71	0.614	23.271
Cost of IT operation	Org.	771/189	80.31	0.749	29.784
Less Internet availability	Org.	682/278	71.04	0.658	26.454
Usefulness in education	Org.	751/209	78.23	0.871	51.367
Cloud control ability	Org.	677/283	70.52	0.643	32.987
Easy implementation	Org.	737/223	76.77	0.815	57.548
Skilled end user	Org.	685/275	71.35	0.468	17.876
Integration	Org.	742/218	77.29	0.572	18.765
Training for staff	Org.	691/269	71.98	0.914	64.568
Energy efficiency	Org.	760/200	79.17	0.764	67.764
Ease of use	Org.	693/267	72.19	0.438	21.876
Quality of service	Tech.	752/208	78.33	0.864	53.876
Affordability	Tech.	679/281	70.73	0.643	49.876
Trust	Tech.	736/224	76.67	0.587	19.765
Complexity	Tech.	699/261	72.81	0.676	27.765
Size of organization	Tech.	729/231	75.94	0.657	25.864
Compatibility	Tech.	678/282	70.62	0.653	25.765
Culture of organization	Tech.	751/209	78.23	0.853	49.658
Service availability	Tech.	688/272	71.67	0.893	217.987
Resource need	Tech.	693/267	72.19	0.753	89.875
Dependence on service provider	Tech.	755/205	78.65	0.427	23.987
Results demonstrable	Tech.	679/281	70.73	0.532	54.634
IT resource	Tech.	737/223	76.77	0.874	47.183
Technological infrastructure	Tech.	699/261	72.81	0.943	89.542
Technological readiness	Tech.	742/218	77.29	0.743	75.432
Service provider support	Tech.	691/269	71.98	0.901	117.075
Regularity	Ext.	760/200	79.17	0.617	25.457
Government pressure	Ext.	693/267	72.19	0.911	85.456
External pressure [a]	Ext.	752/208	78.33	0.678	27.548
Peer pressures	Ext.	679/281	70.73	0.742	29.896
Socio-economic status	Ext.	736/224	76.67	0.497	21.876
Awareness	Ext.	667/293	69.48	0.581	19.765
Cost of access	Ext.	722/238	75.21	0.673	26.765
Cost reduction	Ext.	741/219	77.19	0.945	118.357

[a] "External pressure" appears as an individual survey item in addition to the seven external-pressure factors of the model.

The regression coefficients discriminate much more strongly between factors than the endorsement proportions. The standardised coefficients ranged from 0.427 (dependence on the service provider) to 0.967 (integrity maintenance); 15 of the 43 items had $\beta \geq 0.8$, 19 had $0.6 \leq \beta < 0.8$ and 9 had $\beta < 0.6$. The strongest associations were found for integrity maintenance (0.967), cost reduction (0.945), technological infrastructure (0.943), encryption (0.917), training for staff (0.914), government pressure (0.911), service provider support (0.901) and unauthorised access (0.896). The weakest

were dependence on the service provider (0.427), ease of use (0.438), skilled end user (0.468), data security (0.496), socio-economic status (0.497) and results demonstrability (0.532).

A notable feature is that the two indicators are essentially unrelated: the correlation between endorsement proportion and β across the 43 items is r = −0.03. Integrity maintenance, for example, was endorsed by the fewest respondents (68.44%) yet had the strongest association with adoption (β = 0.967), whereas dependence on the service provider was widely endorsed (78.65%) but had the weakest association (β = 0.427). This divergence is plausible: widely recognised concerns, such as dependence on a provider, may be regarded as an accepted consequence of any cloud migration and therefore do not differentiate respondents who favour adoption from those who do not, whereas less frequently mentioned but technically specific factors, such as integrity maintenance, strongly separate the two groups. For decision-makers, the practical implication is that the frequency with which a concern is voiced is a poor guide to its influence on adoption; prioritisation should be based on the strength of association.

Because all coefficients were positive, the hypotheses that predicted a negative influence—for example, those for unauthorised access, insufficient skilled staff, service availability and dependence on the service provider—are not supported in their hypothesised direction. The results instead indicate that these factors are salient considerations that are positively associated with the adoption construct. This outcome is consistent with the interpretation that respondents who are more attentive to security and operational issues are also those more engaged with, and more favourable to, the adoption of cloud services, rather than with an interpretation in which these concerns directly deter adoption.

4.3 Comparison across perspectives

Table 4 aggregates the factor-level results by perspective. The mean endorsement is almost identical for the four perspectives (74.36–74.87%), so respondents did not systematically regard one group of factors as more relevant than another. The mean standardised coefficient, however, differs clearly: security (0.788) > technical (0.733) > external pressure (0.706) > organisational challenge (0.688). The security perspective combines the highest mean with the single strongest factor (integrity maintenance) and three further factors with β > 0.86 (encryption, unauthorised access and privacy maintenance). The difference between the security and organisational-challenge perspectives, 0.100 in mean β, corresponds to a 14.5% higher mean coefficient for security [(0.788 − 0.688)/0.688 = 0.145].

Table 4. Summary of results by perspective (derived from Table 3).

Perspective	Items	Mean E (%)	E range (%)	Mean β	β range	Strongest factor (β)
Security	8	74.77	68.44–81.77	**0.788**	0.496–0.967	Integrity maintenance (0.967)
Organisational challenge	12	74.84	70.52–80.31	0.688	0.438–0.914	Training for staff (0.914)
Technical	15	74.36	70.62–78.65	0.733	0.427–0.943	Technological infrastructure (0.943)
External pressure	8[a]	74.87	69.48–79.17	0.706	0.497–0.945	Cost reduction (0.945)

[a] Including the "External pressure" survey item.

Within the organisational-challenge perspective, training for staff (β = 0.914) and usefulness in education (0.871) dominate, whereas ease of use (0.438) and skilled end user (0.468) are among the weakest factors overall. This suggests that institutions perceive the capability of their own staff to operate cloud services as more decisive than the usability of the services for end users—a finding that points to targeted staff training as a lever for adoption. In the technical perspective, the prominence of technological infrastructure (0.943), service provider support (0.901) and service availability (0.893) reflects the dependence of cloud-based e-learning on reliable connectivity and provider support. In the external-pressure perspective, cost reduction (0.945) and government pressure (0.911) are the strongest factors, indicating that financial benefits and policy direction are the principal external drivers, while socio-economic status (0.497) and awareness (0.581) are comparatively weak.

These results are broadly consistent with earlier HEI studies that identified service availability, cloud control ability, resource need and staff training as main factors [8], and with qualitative evidence that cost reduction acts as a driver while privacy and control are central concerns [26]. The present results add that, in the Indian context studied, data-integrity and encryption concerns are the factors most strongly associated with adoption, which motivates the security and resource-management measures evaluated in the following subsections.

4.4 Processing time of the proposed and existing PSO allocation

Table 5 and Fig. 2 compare the processing time of the proposed PSO allocation with that of the existing PSO method on a single server. Processing time increases with file size for both methods, from 238.09 s to 975.26 s for the proposed method and from 286.3 s to 1269.1 s for the existing method as the file size grows from 10 MB to 100 MB. The proposed method required less time for every file size. The reduction, calculated with Eq. (6), ranged from 12.37% (30 MB) to 23.15% (100 MB) and averaged 17.52% over the ten file sizes; for the complete workload, the total processing time fell from 6,900.34 s to 5,609.50 s, a reduction of 18.71%.

Table 5. Processing time (s) of the proposed and existing PSO-based allocation on one server, with absolute and relative reduction.

File size (MB)	Proposed (s)	Existing (s)	Reduction (s)	Reduction (%)
10	238.09	286.30	48.21	16.84
20	268.30	329.61	61.31	18.60
30	338.07	385.80	47.73	12.37
40	428.38	502.00	73.62	14.67
50	512.45	590.60	78.15	13.23
60	571.00	680.03	109.03	16.03
70	658.90	808.47	149.57	18.50
80	750.90	941.13	190.23	20.21
90	868.15	1107.30	239.15	21.60
100	975.26	1269.10	293.84	**23.15**
Total	**5609.50**	**6900.34**	**1290.84**	**18.71**

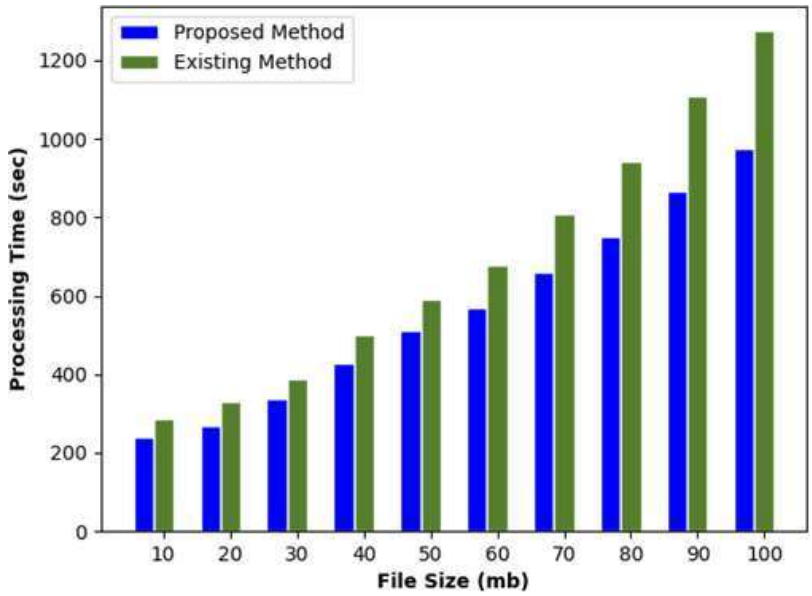


Fig. 2. Processing time of the proposed and existing PSO-based methods for file sizes of 10–100 MB on one server.

The advantage of the proposed method grows with file size. Fitting a straight line to the data gives a marginal processing cost of approximately 8.27 s/MB for the proposed method and 10.95 s/MB for the existing method (coefficients of determination 0.988 and 0.973), i.e. about 24.5% less additional time per megabyte [(10.95 − 8.27)/10.95 = 0.245]. Consequently, the absolute saving increases from 48.21 s at 10 MB to 293.84 s at 100 MB. From an engineering standpoint, this behaviour indicates that the benefit of the optimised allocation lies mainly in the handling of large, computationally demanding files, for which assigning the request to a better-matched VM—in terms of processing speed relative to the file length (Eq. (4))—has the greatest effect. The small, non-monotonic variation of the relative reduction at small file sizes (e.g. 18.60% at 20 MB versus 12.37% at 30 MB) is consistent with the stochastic nature of PSO and with fixed per-request overheads that weigh more heavily for small files. For e-learning services in which learners download or submit large multimedia resources—recorded lectures, simulations and project files—a reduction of roughly one-fifth in processing time translates directly into shorter waiting times and higher throughput for the same infrastructure.

4.5 Effect of the number of servers

Table 6 and Fig. 3 show the processing time of the proposed method with one to four servers. For every file size, processing time decreases as servers are added. Relative to one server, two servers reduced the total processing time by 15.51%, three servers by 34.35% and four servers by 54.59%. With four servers, the reduction ranged from 45.52% (20 MB) to 59.48% (100 MB), corresponding to speed-ups of 1.84 to 2.47. The marginal processing cost also falls with the number of servers, from 8.27 s/MB with one server to 6.37, 4.95 and 3.11 s/MB with two, three and four servers, respectively.

Table 6. Processing time (s) of the proposed method for one to four servers, with reduction relative to one server and speed-up for four servers.

File size (MB)	1 server	2 servers	3 servers	4 servers	Reduction, 4 vs 1 (%)	Speed-up S_4
10	238.09	207.38	171.17	128.10	46.20	1.86
20	268.30	219.10	198.07	146.16	45.52	1.84
30	338.07	298.00	231.25	178.00	47.35	1.90
40	428.38	388.12	268.03	197.40	53.92	2.17
50	512.45	442.55	322.10	222.10	56.66	2.31
60	571.00	511.00	391.00	271.00	52.54	2.11
70	658.90	598.40	468.03	298.90	54.64	2.20
80	750.90	650.20	501.90	340.11	54.71	2.21
90	868.15	689.08	550.27	370.11	57.37	2.35
100	975.26	735.74	580.82	395.13	**59.48**	**2.47**
Total	**5609.50**	**4739.57**	**3682.64**	**2547.01**	**54.59**	**2.20**

The scaling is clearly sub-linear. With four servers the speed-up of 2.47 at 100 MB corresponds to a parallel efficiency of 0.62, and at 10 MB the efficiency is only 0.47 (speed-up 1.86). The two-server configuration is particularly inefficient: it reduces total processing time by only 15.51%, whereas adding a third and a fourth server yields successive further reductions of 18.84 and 20.24 percentage points. Several engineering factors can explain this pattern. Part of the processing time—request queuing, VM scheduling and data transfer over a shared bandwidth of 1,000 units—does not decrease with the number of servers; the heterogeneous VM speeds (250–300 MIPS) mean that added capacity is not uniform; and a single large file cannot be split across servers, so the benefit of additional servers appears mainly as the ability to process more requests concurrently. The rising efficiency with file size indicates that fixed overheads are amortised more effectively for larger files.

For capacity planning of an institutional e-learning cloud, these results suggest that the number of servers should be chosen according to the expected file sizes and request volumes: for workloads dominated by large multimedia files, scaling from one to four servers more than halves processing time, whereas for small files the gains are smaller. Because cloud resources are billed on a pay-per-use basis, the diminishing efficiency of additional servers must be weighed against their cost, and elastic scaling—adding servers only during peak demand—is likely to offer the most cost-effective configuration.

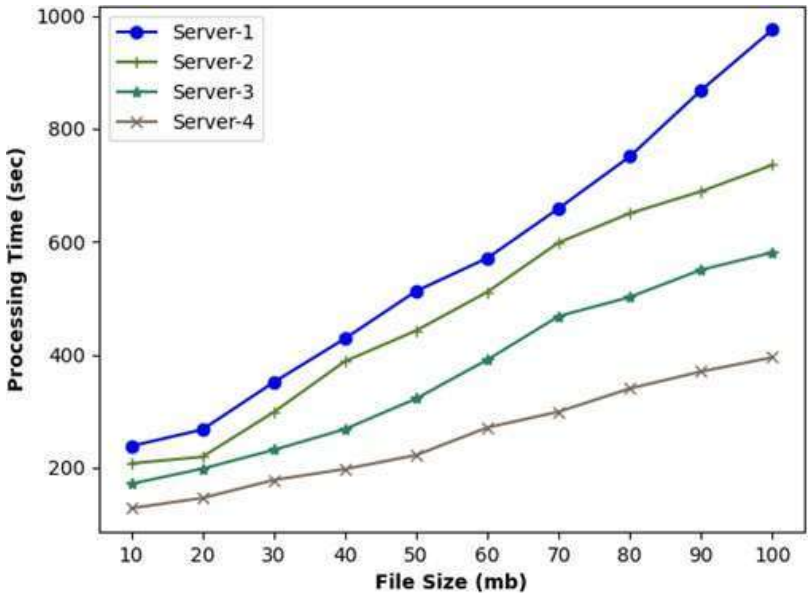


Fig. 3. Processing time of the proposed method for file sizes of 10–100 MB with one to four servers.

4.6 Discussion and limitations

Taken together, the two parts of the study provide a consistent picture. The survey shows that security-related factors, especially integrity maintenance and encryption, and infrastructure- and cost-related factors are the strongest correlates of cloud adoption in the institutions studied. The simulation shows that a framework that encrypts learner files and allocates them with PSO can reduce processing time by about one-fifth relative to an existing PSO scheme, and that scaling to four servers more than halves processing time for the workloads considered. The framework therefore addresses both the security concerns and the resource-efficiency concerns that the survey identified as influential.

Several limitations should be noted. The survey used convenience sampling in one region of India, so the results may not generalise to other regions or institution types, and the factor-level regressions examine each factor individually rather than in a joint structural model, so they do not control for correlations among factors. The endorsement indicator is based on binary responses and may not capture intensity of opinion. In the simulation part, the processing-time comparison was performed with one server, the reported values are single-run results without variance estimates, the overhead of RSA encryption and decryption was not quantified separately, and the results were obtained in simulation rather than on a production e-learning platform.

5. CONCLUSIONS

The present study investigated cloud-based e-learning in higher education from two complementary angles: the determinants of institutional adoption and the efficient, secure processing of learner files in the cloud. The main conclusions are as follows:

(1) The four-perspective model of 42 factors was reliable and valid in a sample of 960 respondents from HEIs and technical colleges in North India ($\alpha = 0.92–0.95$, CR = 0.93–0.95, AVE = 0.67–0.82).

(2) All factors were significantly associated with adoption ($p < 0.001$). The strongest associations were for integrity maintenance ($\beta = 0.967$), cost reduction (0.945), technological infrastructure (0.943) and encryption (0.917); the weakest were for dependence on the service provider (0.427), ease of use (0.438) and skilled end user (0.468).

(3) The security perspective had the highest mean coefficient (0.788), 14.5% higher than the organisational-challenge perspective (0.688), whereas endorsement proportions were nearly identical across perspectives (74.4–74.9%) and unrelated to the strength of association ($r = -0.03$).

(4) The proposed PSO-based allocation reduced single-server processing time by 12.4–23.2% relative to an existing PSO method (18.7% for the total workload), with the largest savings for large files.

(5) Increasing the number of servers from one to four reduced processing time by 45.5–59.5% (speed-up 1.84–2.47), with sub-linear scaling that improves with file size.

SCOPE FOR FUTURE WORK: Future work will validate the adoption model with probability sampling and structural equation modelling across multiple regions, quantify the cryptographic overhead, compare the proposed allocation with other metaheuristics under repeated simulation runs, and deploy the framework on an operational e-learning platform.

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