International Journal of Advanced Engineering and Technology
www.allengineeringjournal.com
ISSN: 2456-7655
Received: 17-10-2025, Accepted: 18-11-2025, Published: 03-12-2025
Volume 9, Issue 2, 2025, Page No. 23-28

Product data management adoption in manufacturing industries: A TOE framework approach

Dandge Shivdas N[1], Swapnil Jain[2], Ganesh Jadhav[3]
[1] Research scholar, Department of Mechanical Engineer, Kalinga University, Raipur, Chhattisgarh, India
[2] Research Guide & Associate Professor, Department of Mechanical Engineer, Kalinga University, Raipur, Chhattisgarh, India
[3] Research Co-Guide & Associate Professor, Department of Mechanical Engineer, D Y Patil Institute of Engg, Mgt & Research, Pune, Maharashtra, India
DOI: https://doi.org/10.66856/ijaet.2025.9.1.10044

Abstract
Product Data Management (PDM) systems have become a critical component of modern manufacturing by enabling organizations to efficiently manage product-related information throughout the product lifecycle. This study investigates the key factors influencing PDM adoption in manufacturing industries using the Technology–Organization–Environment (TOE) framework. A quantitative research design was adopted, and data were collected through a structured questionnaire consisting of 37 items administered to professionals from 48 manufacturing organizations. A total of 189 valid responses were analyzed using SPSS 22.0 and AMOS 22.0. The study employed reliability analysis, KMO and Bartlett's tests, factor analysis, multicollinearity analysis, correlation analysis, and other statistical techniques to validate the proposed model. The findings indicate that technological capabilities, organizational readiness, top management support, perceived value, functional coverage, and external environmental factors significantly influence the successful adoption of PDM systems and contribute to improved operational performance. The results further demonstrate that organizations implementing PDM systems experience enhanced collaboration, efficient product information management, improved productivity, better decision-making, and stronger competitive advantage. The study provides practical insights for manufacturing firms seeking to implement PDM solutions and contributes to the growing body of knowledge on enterprise digital transformation and product lifecycle management.

Keywords: Product data management (PDM), Technology–Organization–Environment (TOE), Product Lifecycle Management (PLM), manufacturing industry, operational performance, digital transformation

Introduction

As a consequence of technical developments, greater products complexity, & increasing global competitiveness, the manufacturing sector has undergone a fundamental transition over the course of the last three decades. Managing product information over the whole product lifetime, from the initial moment of purchase to the point of manufacture, is something that companies need to do in order to maintain their competitive edge in today's market. Problems with the creation of products, delayed releases, quality issues, a lack of cooperation across departments and divisions, and a reduction in the company's overall performance are all potential outcomes that may be brought about by ineffective product management within an organization. [1]

PDM systems were established in order to deal with these challenges. These systems are responsible for storing, organising, and sharing product data throughout the product lifecycle. [2] Product design and engineering, production, quality control, procurement, & after-sales support are all areas that make use of PDM in order to ensure that authorised users are provided with information that is both correct and comprehensive. [3]

PDM systems are now able to handle CAD files and engineering papers at the enterprise level. These systems are enterprise-wide information management solutions. Bills of materials, engineering revisions, workflow modifications, supplier data, quality records, and compliance paperwork are some of the items that people who are now using PDM systems are responsible for managing. [4] With the use of the PLM system, which is a component of PDM system that is now in use, companies are able to grow and enhance their products, communicate more effectively, adhere with laws, and make better choices.[5]

As product development has become more complicated and engineering information management has become more important, PDM solutions have arisen to meet these demands. Product information was kept using paper drawings, engineer documentation, plus manual recordkeeping before PDM. [6] As production methods and product designs grew more complex, these tactics worked for basic commodities but became less successful. CAD technologies popularised in the 1980s increased engineering productivity. These technologies also created a lot of digital item data that needed to be organised and maintained. In response to this tendency, software solutions were created to centralise CAD data, technical drawings, document versions, or product structure. These early systems would form the basis of modern Product Data Management solutions. [7]

In the early 1990s, commercial PDM systems responded to engineering data management needs. Document management, controlled access, and technical information storage & version control were its main goals. Businesses may create a single product data source to avoid duplication, design inconsistencies, and engineering mistakes across all divisions. Thanks to CAD connectivity, engineers could receive the latest product models, preserve revision histories, and track engineering modifications. These skills profoundly enhanced design, manufacturing, and quality. [8]

Late in the 1990s and early 2000s, PDM systems were employed for more than only technical document management. This resulted from worldwide industrial collaboration. Businesses needed integrated solutions to handle BOMs, Engineering Changes Orders, workflow automation, source information, quality documentation, and regulatory compliance records. When this happened, PDM systems went from simple file management to EWIM systems that allowed functional groups to collaborate on projects. Instead of a file manager, they became a consultant who coordinated product development throughout the company. With this breakthrough, connecting to ERP systems became easier, allowing engineers and production to easily communicate information. [9]

PLM, a new phenomenon in the early 2000s, changed PDM. PLM, which retains information throughout the product lifetime from concept to design, manufacture, servicing, and retirement, required PDM, not an engineering database. PDM systems are incorporating IoT, digital twins, and advanced analytics. Other components of these tools include cloud computing, virtual collaboration, digital processes, real-time data interchange, and interface with new technology. These innovations have helped manufacturing companies improve product traceability, development cycles, cross-functional collaboration, and business decisions in aggressive global markets.[10]

There has been a substantial amount of work that has been published in academic journals and empirical research that has been carried out on EIS in industrial enterprises over the course of the prior three decades. In addition, in order for companies to achieve success in the implementation process, they need to have an awareness of the dynamics of technology adoption along with the technical quality of the technology. The combination of organisational, technical, and environmental elements is what will determine the level of success that this endeavour achieves. The literature on the adoption of business systems has said for a considerable amount of time that technological considerations are not sufficient. This is due to the fact that technical criteria alone are not sufficient to account for the adoption and results of such systems. Each factor of adoption affects adopting conduct. [11]

Researching the adoption of various business technologies, such as enterprise resource planning (ERP), customer relationship management (CRM), supply chain management (SCM), and e-commerce platforms, has shown to be quite effective when using this method. It seems to be illustrative, according to the results. [12]

To explain how people's views of the utility and simplicity of a technology may be used to predict whether or not they would accept it, Davis (1989) presents an alternative perspective in the form of the Technology Acceptance Model (TAM). This model illustrates how people's perceptions of a technology can be used to identify whether or not they would embrace it. It is not utilised by as many people as it is when individuals embrace technology at the individual level. This is due to the fact that it does not adequately reflect the organisational and environmental variables that are required when making the decision to install an enterprise system. [13]

Research Methodology

When it comes to statistically assessing the "variability of focused features of populations" (Yin, 2003), the survey approach is the most suited option among the options that were studied. Information is gathered via the act of asking questions, which is what this phrase refers to. When it comes to technologies such as PDM, however, respondents were pre-identified prior to the survey based on their knowledge and role as PDM stakeholders. It is possible to collect the required data using a variety of methods, including but not limited to telephone interviews, mail surveys, or a study of the established literature (Gable, 1994). To gather their thoughts, however, the majority of people these days choose to utilise online polls. Following the collection of the responses, the data was subjected to statistical statistical analysis.

- **Survey instrument development**

We devised this poll in order to get insight into the opinions of individuals on the use of PDM systems by manufacturing businesses. The total number of questions is 37, and they are distributed among three sections:

In Part A of the respondent information, detailed information on the respondent was supplied. This included information about his job and his history. Outside of the firm, including information on the name of the company and its location, among other things.

One of the questions in the third part, which was titled "General information," enquired about the company's revenue, the number of employees, and the amount of available ES.

There are a total of 34 questions about the operational performance of the organization that are included in Part C of the PDM Adoption. Additionally, there are various T-O-E context constructs. Each of the questions in Parts B and C were answered using a Likert scale with seven points. The Likert scale was used since it was developed to be simple and straightforward for the participants to comprehend. In addition, the seven-point scale was chosen because of the fact that the responses were of a bipolar nature. The usage of a seven-point scale was chosen because, according to Shah and Goldstein (2006), it maximises reliability while simultaneously increasing the range of responses. A total of seven potential responses were provided on the scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The middle number, which was the 4-Neutral value, was it. During the development of the questionnaire, the goal was to make it simple for respondents to understand and fill out. The phenomenon that was going to be investigated, on the other hand, was not in any way compromised.

- **Pilot study**

Initially, a pilot study was carried out in order to guarantee that the questionnaire would be simple to read and understand. Additionally, there was a focus on the genuineness of the material. The survey questions were examined in great depth by professionals working in product data management systems as well as a limited number of academics from institutions that have experience in the administration of advanced manufacturing technologies and methods. The conversation was beneficial in terms of maintaining the high-quality, goal-relevant, and issue-focused nature of the questionnaire to be completed. The questionnaires were subjected to insignificant modifications, the majority of which consisted of the elimination or consolidation of particular questions and the rephrasing of certain terms.

- **Survey Sample Design**

This study was conducted using a random sample approach to exclude any possibility of sampling error occurring throughout the process. Using this method of sampling, each individual item from the population that is being provided is given an equal chance of being included. When doing this kind of study, it is recommended to choose a sample size that is five times more than the total number of components that make up the conceptual architecture. To create a sample, one must first choose a population set, then compile a list of all the components that comprise that population, then devise a sampling mechanism, and lastly settle on a sample size. These are the phases that comprise the sample design process.

- **Survey Administration**

The PDM system is an application that has been granted permission for usage in commercial settings. When you go to the market, you could discover them as goods that are ubiquitous. Therefore, in order to gather answers to the survey, we reached out to the companies that had subscribed to these systems. By tapping into the professional network and online user groups that were associated with the program, it was able to get this information. Online participation in the poll was encouraged due to the ease with which it could be disseminated. The PDM experts or IT directors of these firms were the ones who got the survey and then sent it to the necessary individuals. A total of forty-eight different industries who are knowledgeable with PDM systems were contacted by us. A total of 250 individuals were contacted, and 75.6% of them responded to our inquiry. The research scholar's participation in the professional network for PDM systems was a factor that led to the high response rate attained.

- **Survey Analysis**

Yin (2003) states that data analysis is "a systematic and orderly approach taken towards the collection of the data so that information can be obtained from the data." When drawing conclusions from real-world data and going on to make broad statements, statistical proof is useful. The data was analysed using the AMOS 22.0 software program and the IBM Statistical program for the Social Sciences (SPSS) version 22.0. A plethora of prior studies have made use of these software programs. The survey data was analysed by Dalenogare et al. (2018) and Kamble et al. (2019), for instance, using SPSS.

- **Statistical analysis**

The Cronchbach's alpha, the KMO test, skewness and kurtosis, and confirmatory factor analysis were the statistical methods that we used in order to carry out the preliminary data inspection. SPSS 22.0 and AMOS 22.0 were the software applications that were used in the process of doing the analysis. The chi-square test was used in order to ascertain whether or not the variables in the list were dependant on one another. ANOVA, factor analysis, and principal component analysis were also used in the analysis that was carried out.

Results

In order to conduct the survey, purposive sampling was used to pick respondents at random from a group that had been preselected. An overall poll was conducted with 227 industry people from 48 different industries. Those who have PDM or prospective responders who have their competence in PDM were chosen for these sectors. We looked for people affiliated with the PDM business by searching professional networking platforms and PDM community organisations.

Data about the manufacturing industry that makes use of PDM systems was acquired by using the resources that are available on the internet. Department, organization size, and categorisation of the responder are all included in the table.

Table 1: Demographic Profile of Respondents Based on Designation, Department and Organisation Size

Variable	Category	Percentage of Respondents
Designation	Designer	20%
	Asst. Manager	19%
	Jr. Engineer	21%
	Sr. Engineer	17%
	Manager	6%
	Director	2%
	Others	15%
Department	Engineering / R and D	34%
	Sales and Marketing	13%
	IT	22%
	Finance	6%
	Production	14%
	Maintenance	4%
	Supply Chain / Purchase / Logistics	6%
No. of Employees in Organisation	>1000	34%
	250–500	34%
	50–250	19%
	<50	13%

The demographic profile of the respondents was given in Table 4.1 according to designation, department and number of employees in the respondents' organisation. Based on the analysis, the respondents were from various professional positions and departments as this enabled opinions from employees with varying organizational exposure and responsibilities to be collected.

As far as designation is concerned, the largest number of respondents were Junior Engineers (21%), Designers (20%) and Assistant Managers (19%). Senior Engineers made up 17% of the respondents, Managers 6% and Directors 2%. Additionally, 15% of the respondents belonged to other categories. The majority of respondents were from middle and technical level positions, indicating that the data included primarily the views of employees directly involved in operational, engineering and technical activities. The representation for the higher managerial positions (Managers and Directors) were relatively weaker, which suggested that the number of respondents at the strategic level was smaller.

Engineering/R&D department had the highest percentage of respondents (34%), followed by the IT department (22%). Production employees (14%) and Sales and Marketing (13%) were the two largest groups of respondents. The participation of the Finance, Purchase/Logistics departments was 6%, while the lowest participation was from Maintenance at 4%. This distribution gives an idea that the study was primarily on the respondents who were related to technical and innovation related departments. The increased involvement of Engineering/R&D and IT departments is due to their importance in the functioning of the organization and technological development. However, Finance and Maintenance have comparatively weak responses suggesting less representation from functions more supportive of the business.

About 34% worked in a company with 1000 or more workers, and another 34% in one with 250 to 500. 19% of respondents worked for a 50-250-person company, while 13% worked for less than 50. Mainly medium-to-large firms responded. Personnel in mature businesses with well-defined operational procedures and a stronger workforce contributed to the study's conclusions.

Demographics showed respondents from all organisational levels, divisions, and sizes. The study applies to industrial and corporate organisational and operational perspectives since technical specialists and medium and large enterprises are widespread.

- **Analysis Of Missing Values**

Missing value analysis was used to find missing data and distribution patterns. We reviewed all answers. All replies above zero on the one-to-seven scale were confirmed. In this study, no missing values were found.

- **Unengaged Response**

The "unengaged response check" is used to detect whether or not respondents finished the survey without providing their best effort or reading it.

The responses would be same if the responder completed all of the questions with similar responses. Participants were presumed to be actively engaged if they provided responses to a variety of questions. It was discovered that the replies had a standard deviation that was not zero. At this point, it seemed like nobody was taking it easy.

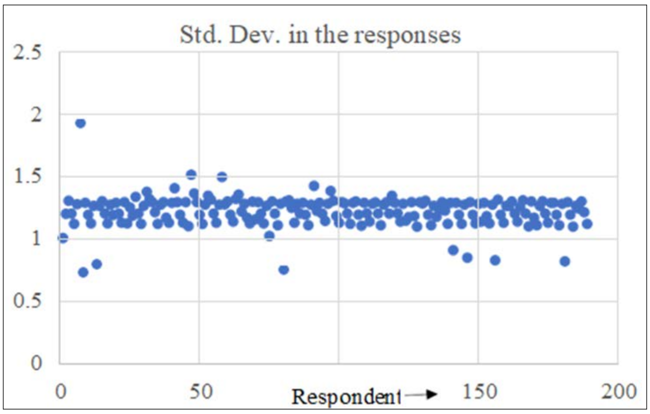

Fig 1: Analysis of disengaged responses

- **Outlier Analysis**

The purpose of the outlier analysis is to find data points that are very out of the ordinary. The Mahalanobis Distance (MD) is the identifying parameter used for this. This measures how far away a given data point or case is from the center of all the other data points or instances. There were 189 total samples in the research, thus the outlier measure is based on the value (MD/df), which should be more than 3 or 4, according to the literature (Hair et al., 2016). Outliers were not identified in the current investigation since no instance had a score greater than 4. Only a small number of replies had a crucial ratio of 3 or 4, but this did not prevent their inclusion in the study since they could all be linked to valid respondents.

Table 2: Analysis of outliers

Case No	Mahalanobis Distance	MD/df	p value
26	24.5353	3.505043	0.00011
95	24.46986	3.495694	0.00011
107	20.78315	2.969021	0.00022

- **BIAS**

We ran the numbers to see if any respondents who didn't fill out the survey contributed to the overall bias. Approximately 48 people did not answer to the survey after it was sent out to 227 people.

We looked into the non-respondents, but we couldn't find any correlation between them and the other variables. It was observed that several respondents from the same organization had not responded to the survey, and the reasons given for this were,

a. The worker had departed from the company.

b. An employee's undisclosed cause for being unavailable.

Studies by Armstrong and Overton (1977) and Lambert and Harrington (1990) propose analysing late respondents as non-respondents. We compared the replies of the early birds with those of the late birds to see whether there was any evidence of bias. A total of 117 people responded early, while 72 people responded later. To find any significant difference in seven constructions, a simple t-test was used. At the 95% confidence interval, however, no change was seen.

Table 3: Early vs Late response bias

Parameter			**Early respondents**		**Late respondents**		**Confidence interval**
Construct		**Description**	**mean**	**Std dev**	**mean**	**Std dev**	
Perceived Compatibility	PC1	Integration	6.73	0.47	6.78	0.42	95%
	PC2	Information exchange	6.64	0.48	6.67	0.47	95%
	PC3	Knowledge Management	6.33	0.67	6.47	0.58	95%
	PC4	Platform	6.55	0.66	6.65	0.59	95%
Perceived Value	PV1	Operating Cost	5.91	0.77	5.99	0.74	95%
	PV2	Efficiency	6.55	0.59	6.64	0.59	95%
	PV3	Lead Time	6.64	0.67	6.81	0.5	95%
	PV4	Product Quality	6.28	0.64	6.43	0.62	95%
Technical Capability and Security	S1	External interaction	5.68	0.54	5.83	0.56	95%
	S2	Data Sharing	5.3	0.53	5.38	0.62	95%
	TC1	IT Resources	6.35	0.55	6.49	0.53	95%
	TC2	Skilled manpower	6.38	0.52	6.43	0.55	95%
	TC3	Subject matter experts' availability	6.72	0.52	6.82	0.54	95%
Nature of Firm	NF1	Adoption in allied industry	5.56	0.59	5.65	0.61	95%
	NF2	Experience and expertise	5.76	0.54	5.79	0.58	95%
	NF3	Digitization initiatives	6.17	0.46	6.22	0.59	95%
	NF4	Product range	6.42	0.75	6.6	0.6	95%
Top management support and Organisation readiness	TMS1	Size	6.62	0.77	6.79	0.55	95%
	TMS2	Demographic	6.74	0.58	6.83	0.5	95%
	TMS3	MIS	6.31	0.62	6.42	0.69	95%
	OR1	Management commitment	6.49	0.66	6.61	0.62	95%
	OR2	IT strategy	6.75	0.51	6.82	0.54	95%

Functional coverage	FC1	Engineering and R and D	6.88	0.37	6.79	0.58	95%
	FC2	Manufacturing and Services	6.32	0.74	6.46	0.53	95%
	FC3	Sales and marketing	6.14	0.67	6.25	0.55	95%
	FC4	Finance	3.44	1.05	3.5	0.82	95%
External forces and industries	EF1	Industry regulation	1.79	0.92	2.06	1.56	95%
	EF2	Quality Audits	5.79	0.48	5.76	0.57	95%
	EI1	Service industry availability	6.17	0.56	6.22	0.56	95%
	EI2	Competitive pressure	4.18	1.16	4.35	1.02	95%
	EI3	Customer pressure	3.38	0.99	3.5	1.13	95%
Operational Performance	OP1	Profitability	6.18	0.55	6.21	0.53	95%
	OP2	Market Share	6.32	0.54	6.29	0.54	95%
	OP3	Productivity	6.76	0.58	6.79	0.41	95%
	OP4	Work Environment	6.48	0.65	6.32	0.53	95%

- **KMO and barlett's test**

It is vital to determine whether or not the data are appropriate before beginning the process of factor analysis. The Kaiser-Meyer-Olkin (KMO) test should be used in order to determine whether or not the sample size is sufficient (Field, 2009). All the way from zero to 1.0 is the range that this statistic covers. The use of factor analysis is recommended for values that are more than 0.6, as stated by Hair et al. (2016) & Kaiser (1974). According to the data shown in the table, the KMO value for this particular investigation is 0.638.

The Barletts' test is used in order to get an understanding of whether or not the correlation matrix is an identity matrix. It is clear from looking at the table that this test produced a substantial result. There is the possibility of doing factor analysis on the data.

Table 4: The sphericity test by Barlett and KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.638**
Bartlett's Test of Sphericity	**Approx. Chi-Square**	**8653.991**
	Df	595
	Sig.	0.000

- **Test For Multicollinearity**

When we use the test, we look for a connection between observable variables and unseen or independent variables, but we do not look for a connection between independent variables. To get a complete understanding of the model, independent variables are required. It has been established via the multicollinearity test that the independent variables do not exhibit multicollinearity. This is due to the fact that all tolerance values surpassed 0.2. It is confirmed that there is no multi-collinearity among the independent variables since all of the VIF values are lower than 5.0 or above.

Table 5: Test for multicollinearity

	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	**Std Error**	**Beta**			**Tolerance**	**VIF**
(Constant)	2.951	0.544		5.427	0.000		
PC	0.059	0.056	0.007	0.106	0.916	0.825	1.212
PV	0.357	0.065	0.393	5.493	0.000	0.785	1.274
TCS	0.096	0.068	0.010	0.140	0.889	0.787	1.271
NF	0.073	0.082	0.079	0.886	0.376	0.508	1.967
TMSOR	0.133	0.107	0.013	0.124	0.901	0.354	2.824
FC	0.111	0.081	0.012	0.138	0.891	0.514	1.946
EF	0.968	0.071	0.092	1.361	0.175	0.874	1.144

Table 6: Test for correlation

	PC	**PV**	**TCS**	**NF**	**TMSOR**	**FC**	**EF**	**OP**
PC	1							
PV	0.246	1						
TCS	0.321	0.14	1					
NF	0.512	0.12	-0.035	1				
TMSOR	-0.114	0.35	0.125	0.551	1			
FC	0.225	0.23	0.402	-0.163	0.335	1		
EF	-0.103	0.5	0.225	0.554	0.221	0.203	1	
OP	0.412	0.4	0.382	0.402	0.462	0.423	0.501	1

- **Factor Analysis**

According to Mitra and Datta (2014), factor analysis is used to find the unique latent constructs that describe the relationship between the elements in the collection. The major goal is to reduce the number of dimensions in order to get at the underlying constructs or latent variables that explain the items in the collection.

The current study made use of dimensional reduction to uncover variables connected to operational performance and PDM adoption. The samples are assumed to be homogeneous, linear, and normal in factor analysis. Using PCA and varimax rotation, 8 factors were extracted, accounting for 78% of the total variance.

Conclusion

This study examined the adoption of Product Data Management systems in manufacturing organizations using the Technology–Organization–Environment (TOE) framework and identified the key factors influencing successful implementation. The empirical findings demonstrate that technological capability, organizational readiness, perceived value, top management support, functional coverage, and environmental conditions collectively play a significant role in improving PDM adoption and enhancing operational performance. The statistical analyses confirmed the reliability and validity of the research model, indicating that the proposed framework is suitable for evaluating PDM implementation in industrial settings. Organizations adopting effective PDM systems benefit from improved product information management, streamlined workflows, enhanced collaboration across departments, reduced engineering errors, and better decision-making throughout the product lifecycle. These improvements ultimately contribute to increased productivity, product quality, and organizational competitiveness. Despite its contributions, the study is limited to manufacturing organizations and a specific sample of respondents, which may restrict the generalizability of the findings. Future research may extend this work by examining different industrial sectors, larger and more diverse samples, and the integration of emerging technologies such as artificial intelligence, digital twins, cloud computing, and Industry 4.0 to further strengthen Product Data Management systems and support sustainable digital manufacturing.

References

1. Wang L, Yang M, Pathan ZH, Salam S, Shahzad K, Zeng J. Analysis of influencing factors of big data adoption in Chinese enterprises using DANP technique. Sustainability,2018:10(11):3956.
2. Tawiah V. The effect of IPSAS adoption on governance quality: Evidence from developing and developed countries. Public Organization Review,2023:23(1):305–324.
3. Schaper LK, Pervan GP. ICT and OTs: A model of information and communication technology acceptance and utilisation by occupational therapists. International Journal of Medical Informatics,2022:76:S212–S221.
4. Thottoli MM, Thomas KV. Characteristics of information communication technology and audit practices: Evidence from India. VINE Journal of Information and Knowledge Management Systems,2022:52(4):570–593.
5. Shahid NU, Sheikh NJ. Impact of big data on innovation, competitive advantage, productivity, and decision making: Literature review. Open Journal of Business and Management,2021:9(02):586.
6. Van Dyk R, Van Belle JP. Factors influencing the intended adoption of digital transformation: A South African case study. 2019 Federated Conference on Computer Science and Information Systems (FedCSIS), Leipzig University in Leipzig, Germany IEEE, 2019, 519–528.
7. Verma S, Chaurasia S. Understanding the determinants of big data analytics adoption. Information Resources Management Journal (IRMJ),2019:32(3):1–26.
8. Rantanen T, Lehto P, Vuorinen P, Coco K. The adoption of care robots in home care—a survey on the attitudes of Finnish home care personnel. Journal of Clinical Nursing,2018:27(9–10):1846–1859.
9. Verma S, Bhattacharyya SS, Kumar S. An extension of the technology acceptance model in the big data analytics system implementation environment. Information Processing & Management,2018:54(5):791–806.
10. Verma S, Bhattacharyya SS. Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. Journal of Enterprise Information Management,2017:30(5):354–382.
11. Safari N, Safari F, Kazemi M, Ahmadi S, Hasanzadeh A. Prioritisation of cloud computing acceptance indicators using fuzzy AHP. International Journal of Business Information Systems,2015:19(4):488–504.
12. Qureshi MO, Syed RS. The impact of robotics on employment and motivation of employees in the service sector, with special reference to health care. Safety and Health At Work,2014:5(4):198–202.
13. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly,2003:27(3):425–478.