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ARTICLE

How Computer-Based Knowledge Repositories Enhance Organizational Memory: An Attempt to Generalize a Failure Organizational Learning Model Based on Two Anonymous Surveys

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Abstract

This study aims to clarify the mechanism by which organizational memory is enhanced through computerized recording and the facilitation of organizational members' memory in organizations, asking how computer-based knowledge repositories, learning records, and human memory contribute to organizational memory in learning from failure. We conduct a statistical analysis of quantitative data collected over 2 years through questionnaires administered to employees working in Japanese companies, to examine and generalize the model previously constructed through case studies. The findings reveal that computer-based knowledge repositories do not directly enhance organizational memory but rather enhance organizational memory by facilitating the act of recording. It further reveals that the use and recording of computer-based knowledge repositories and human memory are enhanced when they are of interest to organizational members. The significance of this study is that it deepens understanding of how to utilize computer-based knowledge repositories in organizations for organizational learning from failures, expected to prevent the recurrence of failures, and consequently, to improve organizational performance.

Keywords Organizational learning · Failure · Computer usage · Organizational memory

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1 Introduction

Organizational failure is sometimes repeated. For individuals, it may be possible to avoid the same failure if they reflect on their failure and take countermeasures. However, in an organization, even if an individual organizational member reflects on the failure, another member may make the same failure. In addition, for a repetitive task that is part of routine work in an organization, operations may be performed without awareness that they could lead to failure. When a failure occurs in an organization, a review meeting is often held and measures are devised to prevent the failure. However, such measures might not be circulated within the organization to enable all organizational members to adopt them. Even if they were circulated within the organization, they could be forgotten or diluted over time. In such cases, the same failures that occurred previously within the organization will occur again.

Measures to prevent the recurrence of failures in an organization undergo a thorough investigation of the process leading up to the failure through a review meeting. Problems and issues are clarified, solutions to these problems and issues are formulated as preventive measures, and are disseminated within the organization and memorized by the organization members. The review meeting process is commonly recorded as a report. Depending on the organization, this record may be on paper or in a computerized database (often called a knowledge repository or knowledge-sharing infrastructure) for retrieval by members of the organization.

The fact that similar failures occur repeatedly in an organization may mean that measures to avoid failure are inadequate or that they have not been embedded in organizational memory owing to inadequate recording or memory.

This study aims to clarify the mechanism by which organizational memory is enhanced through computerized recording and the facilitation of organizational members' memory in organizations. The results can be used to prevent the recurrence of failures in organizations and contribute to improving organizational performance.

We conduct a statistical analysis of quantitative data collected over 2 years through questionnaires administered to employees working in Japanese companies. The findings reveal that computer-based knowledge repositories do not directly enhance organizational memory but rather enhance organizational memory by facilitating the act of recording. The study further reveals that the use and recording of computer-based knowledge repositories and human memory are enhanced when they are of interest to organizational members. We suggest that while enhanced human memory enhances organizational memory, the use of computer-based knowledge repositories does not necessarily enhance human memory.

The significance of this study is that it deepens understanding of how to utilize computer-based knowledge repositories in organizations for organizational learning from failures, which is expected to prevent the recurrence of failures, and consequently, to improve organizational performance.

This paper is an extension of Nagayoshi and Nakamura [1], which not only reviews previous studies carefully but also carefully describes the process of data collection and analysis of the collected data. It also attempts to make the findings more convincing by discussing the results of the analysis in more detail.

The rest of this paper is structured as follows. In the next section, we review previous studies and describe the research gap. Then, we identify the research questions. The following section develops the hypotheses. Then, we present the research methodology, data collection, and the results of the data analysis. The next section presents and discusses the results of the data analysis. The final section concludes.

2 Literature Review

2.1 Definition of Failure

According to Hatamura [2], who studies failures and their countermeasures from an engineering perspective, failure is "a human action that does not reach a defined goal" or "an undesirable and unexpected result of a human action." There are two types of failures: worthwhile and worthless. A worthwhile failure is "a failure that cannot be avoided even with great care" and is a step into the unknown. "Worthless failures" are "failures other than worthwhile failures."

Iske [3] refers to failures as "brilliant failures," because they are organizational attempts to create value but fail to produce the results originally intended. He classifies these "glorious failures" into two categories: serendipity, or the accidental discovery of something important; and an unplanned outcome, which may lead to another desirable result or a valuable learning experience.

Edmondson [4] lists three typical examples of failures: avoidable, complex, and smart. Avoidable failures are those that deviate from a known process; cause an unwanted outcome; and are attributed to a lack of action, skill, or attention. Complex failures are those in which an unprecedented and unusual combination of events and actions leads to an unwanted outcome, and are caused by the addition of complexity, variety, and unprecedented factors to a familiar situation. A wise failure is one in which a new thing is started and an unwanted result occurs, and is attributed to uncertainty, attempts, and risk-taking.

2.2 Importance of and Challenges in Failure Research

Madsen and Desai [5] state that organizations are more effective in learning from failure than from success, that knowledge gained from failure amortizes more slowly than knowledge gained from success, and that how effectively an organization can learn from different forms of experience is affected by the accumulation of prior experience, the size of which affects how effectively an organization can learn from different forms of experience.

Syed [6] refers to the inside story of how success occurs and how we cannot grow unless we are prepared to learn from our mistakes. To this end, the medical and airline industries, global corporations, and professional sports teams form part of the many case studies related to failure, thereby revealing the structure of failure.

Unlike individuals learning from failure in organizations, many companies and organizations are not good at it [7, 8]. One reason is that the organizational members who caused the failure seek their own self-preservation and psychological safety, which prevents them from acquiring knowledge. In other words, publicizing the process leading to failure has a psychological burden and a negative impact on visible reputation in terms of compensation and status by being identified among organizational members and held accountable for the failure [4]. Edmondson [4] analyzes various case studies, including Pixar, Volkswagen, and the Fukushima nuclear power plant, to argue how interpersonal insecurity undermines organizations and the importance of psychological safety in organizations to overcome it. Syed [9] suggests that to detect fatal failures before they occur and increase productivity, it is important to have cognitive diversity that embraces diverse ways of thinking and avoids insularity. and freeing employees' thinking from insularity and blind spots.

2.3 Organizational Learning Process

Organizational learning from failure is positioned as organizational learning, which Huber [10] defines as "learning by the subject when the subject's potential range of behavior is changed through information processing." He reviews previous studies on organizational learning and identifies four processes: knowledge acquisition, information distribution, information interpretation, and organizational memory. As most previous studies on organizational learning refer to knowledge acquisition, it is clear that for organizational learning, the knowledge to be acquired must be disclosed. The literature also mentions the usefulness of computer utilization in organizational memory.

2.4 Organizational Memory and Organizational Routines

Organizational memory, a process of organizational learning, is a means of storing knowledge for future use [10]. Organizational memory can be divided into "data storage" and "data withdrawal" [11]. Two additional means of "data storage" are possible. One is to store the data in the memory of individuals who constitute the organization, and the other is to record data using documents, computers, and other objects and tools. Stored data are retrieved when needed. Cognition and other factors shared by organizational members are thought to play an important role in effective data withdrawal [12–14], but the relationship with information technology is not yet clear, and further research is needed.

Simon [15] approaches this topic from the perspective of cognitive psychology. Cohen [16], in exploring the interface between cognitive psychology and organizational theory, mentions the distinction between procedural and declarative memory, while Cohen and Bacdayan [17] show through laboratory experiments that organizational routines emerge and elements are stored as procedural memories.

Takahashi [18] extends the routine-based organizational learning theory of Levitt and March [19], who consider the existence of routines as the basis of organizational learning and organizational memory, and the importance of the persistence of organizational routines for organizational performance improvement.

2.5 Computer Applications and Memory

Huber [10] suggests that computers are helpful for organizational memory.

Sparrow et al. [20] and Wegner and Ward [21] divide participants with access to the Internet and those without access into two groups, asking them miscellaneous questions, followed by a memory task. Participants who had access to the Internet had lower recall of the contents of the questions, but higher recall of where to go to access them. Information easily obtained through online searches using Internet search engines tends to be easily forgotten; this phenomenon is referred to as the "Google effect" or "digital amnesia."

Greenfield [22] discusses the potential of Internet-related technologies to erode human memory by analyzing the direct effects of social networking, surfing the Internet, and video games on the brain from a scientific perspective.

Using a questionnaire survey and statistical analysis, Nagayoshi and Nakamura [23] find that computer-based knowledge repositories may inhibit individual memory in organizational learning from failure. However, using another questionnaire survey and statistical analysis, Nagayoshi and Nakamura [24] find that computer-based knowledge repositories may enhance personal memory. Considering the inconclusive evidence, Nagayoshi and Nakamura [25–27] conduct follow-up studies for further validation. However, these are case studies of companies that perform well in organizational learning from failure and cannot be generalized.

2.6 Knowledge Sharing Motivation and Altruism

Today, knowledge is increasingly recognized as the most important resource in organizations and a key differentiator in business. Knowledge management can lead to innovation in organizations and improve business performance [28].

Knowledge sharing among colleagues is necessary to achieve knowledge creation in organizations. Motivation for knowledge sharing leads to knowledge-sharing behavior. Chang and Chuang [29], Wang and Hou [30], and Chumg et al. [31] suggest that reputation and altruism are extremely valuable rewards for encouraging people to share knowledge.

Lin [32] examines the role of both extrinsic motivators (expected organizational rewards and reciprocal benefits) and intrinsic motivators (knowledge self-efficacy and enjoyment of helping others) in explaining employees' knowledge-sharing intentions. The results indicate that motivational factors, such as mutual benefit, knowledge self-efficacy, and enjoyment of helping others, are significantly associated with employees' knowledge-sharing attitudes and intentions. However, expected organizational rewards have no significant effect on employees' attitudes or behavioral intentions regarding knowledge sharing.

2.7 Research Gap

The importance of research on organizational learning from failure has been recognized and studied. If we consider organizational learning from failure as organizational learning, similar studies have been conducted on the organizational learning process, knowledge-sharing motivation, altruism, and psychological safety. Research has also been conducted on organizational memory, which is important in organizational learning from failure, and some studies further refer to the relationship between human memory and computers.

However, previous research has not sufficiently focused on organizational learning from failure. In particular, clarity is required on the factors that promote computer utilization, why the act of recording is promoted, and why human memory is promoted in organizational learning from failure. The relationships between these factors and computer utilization have been clarified. In this context, studies have attempted to use case studies of companies that have successfully implemented organizational learning from failure; however, further research is needed to generalize the findings.

3 Research Question

The research question for this study is as follows.

RQ How do computer-based knowledge repositories, learning records, and human memory contribute to organizational memory in learning from failure?

4 Hypothesis Development

We construct hypotheses based on previous studies conducted on a Japanese company that excels at organizational learning from failure and related previous studies [25–27]. We also construct a hypothetical model by logically combining the constructed hypotheses.

Monty et al. [33], who study human memory, state that memory is enhanced by the motivation of self-involvement in the subject matter. Thus, we infer that people remember and act because they are interested in the subject matter. This extends Nagayoshi and Nakamura's [25] model, because their model deals only with the relationship between computer-based knowledge repositories, records, and memory; the relationship with the objects of records and memories is not clear. Considering this background, Nagayoshi and Nakamura [26, 27] hypothesize a model that considers whether the object of record or memory is an organizational or individual concern and test the model based on case studies. In this study, we also construct our hypotheses based on Nagayoshi and Nakamura's [26, 27] model.

If issues are of interest to organizational members, such as wanting to prevent failure or not wanting to be involved in failure, it can be inferred that it is easy to encourage them to search for relevant data and information, store data and information in computer-based knowledge repositories, and use the stored data and information. Furthermore, we can infer that if matters are of interest to organizational members, the information may be recorded or people may try to remember it.

Based on the above, we present the following hypotheses.

Hypothesis 1 (H1) *A matter of interest relevant to work strengthens the use of a computer-based knowledge repository.*

Hypothesis 2 (H2) *A matter of interest relevant to work strengthens recording activity.*

Hypothesis 3 (H3) *A matter of interest relevant to work strengthens human memory.*

Nagayoshi and Nakamura [25] develop a hypothetical model based on Huber's [10] review of information as a facilitator of organizational memory. In other words, recording acts that accumulate hard information and memories that accumulate soft information promote organizational memory. Furthermore, Huber [10] mentions the usefulness of computers in organizational memory.

Based on the above, we present the following hypotheses.

Hypothesis 4 (H4) *A computer-based knowledge repository directly strengthens organizational memory.*

Hypothesis 5 (H5) *A computer-based knowledge repository strengthens recording activity.*

Hypothesis 6 (H6) *A computer-based knowledge repository strengthens human memory.*

Hypothesis 7 (H7) *Recording activity strengthens organizational memory.*

Hypothesis 8 (H8) *Human memory strengthens organizational memory.*

Combining H1–H8, we construct the hypothetical model shown in Fig. 1. The hypotheses and the hypothetical model, described in Nagayoshi and Nakamura [25–27], are also used in this study.

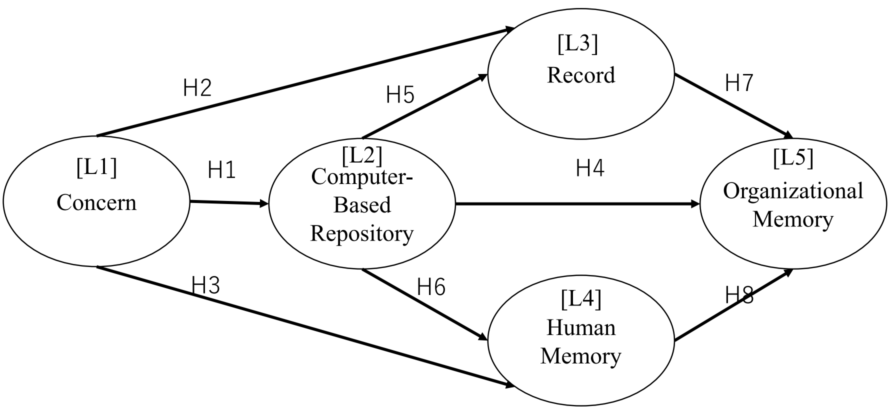

Fig. 1 Hypothetical model

5 Research Methodology, Data Collection, and Analysis

This study was conducted through a hypothesis-testing quantitative analysis. To answer the research question, hypotheses were developed based on previous studies. These hypotheses were then combined to construct a hypothetical model. To test the model, quantitative data were collected from unspecified organizations through an Internet questionnaire. The collected data were subjected to covariance structure analysis using statistical analysis software. The results of the analysis were then examined in detail and discussed to derive the findings. Figure 2 shows the research process.

Two Internet surveys were conducted in September 2022 and March 2023. The surveys were outsourced to iBridge Corporation, and were conducted using a service called Freeasy, provided by the company. The population for these two surveys consisted of men and women aged over 20 years who worked in Japanese companies owned by the corporation, as described in detail in the next subsection.

5.1 Data Collection

5.1.1 Survey Execution

The survey was conducted by iBridge Corporation, a Japanese survey implementation company. The company has 13 million monitors, which is one of the largest numbers of monitors in Japan. The questionnaire consisted of 50 items. The questions were created by the authors based on the hypotheses. The questionnaire was created using Freeasy, a survey platform owned by the company, and administered via the Internet to the company's monitors. As the questionnaire was designed for employees of organizations and companies, occupational attributes were limited to company employees (regular employees), company employees (contract and temporary employees), managers and executives, public officials (excluding faculty members), and doctors and medical personnel. Furthermore, for the same reason, the age range was over 20 years old. The firms were asked to provide a sample of 400 respondents. This decision was made because the collection of approximately 385 samples was sufficient to allow for a 5% margin of error in the data. Table 1 presents a summary of the survey implementation.

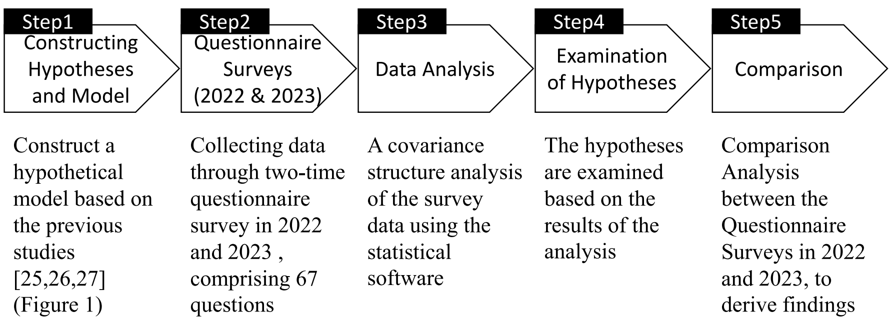

Fig. 2 Research process

The first survey was conducted on August 19, 2022, and the second survey was conducted during March 13–14, 2023. The first survey included a large number of straight-line responses, and thus, an AI-based fraudulent response elimination service provided by the survey provider was added as an option in the second survey. According to the company that conducted the survey, the option would collect 120% of the target sample size and eliminate responses with short response times and straight-line responses as fraudulent responses. If the number of fraudulent responses exceeds 20%, it is not possible to eliminate all fraudulent responses.

5.1.2 Data Cleaning and Sample Analyzed

An overview of the data from the two surveys provided by the data collection company revealed that the data contained straight-line responses; therefore, data cleaning was performed. The authors conducted the data-cleaning process to identify and eliminate responses that selected the same number on the scale for more than 80% of the items for the 50 Likert-scale single-answer questions. This process reduced the number of samples provided by the survey company from 400 to 255 for the first survey and from 400 to 317 for the second survey. In this study, the data were analyzed as sample data.

Figure 3 and Tables 2 and 3 show the age structure, sex, marital status, and occupational attributes of the analyzed data.

Table 1 Questionnaire survey

		1st Survey	2nd Survey
Survey	Number of questions	50	
	Answer format	7-point Likert scale single response (Web survey)	
	Effective date	August 19, 2022	March 13–14, 2023
Respondent attributes	Age	Over 20 years old	
	Occupation	Company employee (full-time), company employee (contract, temporary staff), manager/officer, public official (excluding faculty/staff), doctor/medical professional	
	Number of samples received	400	
Option to eliminate fraudulent responses by the company conducting the survey		No	Yes
Survey conductors	Subcontractor	iBridge Corporation	
	Service name	Freeasy	

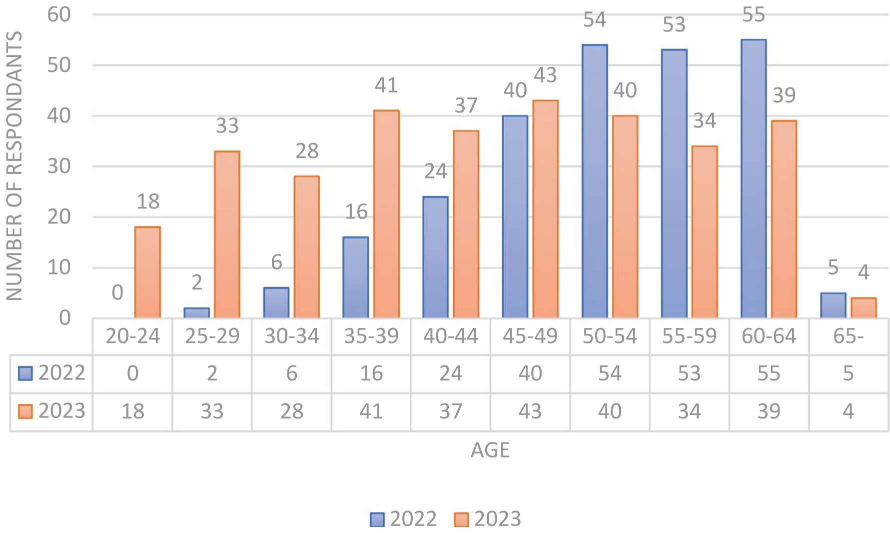

Fig. 3 Age of respondents

Table 2 Sex of respondents

	Female		Male		Total	
	2022	2023	2022	2023	2022	2023
Marriage						
Married	21	66	135	74	156	140
Unmarried	33	95	66	82	99	177
Total	54	161	201	156	255	317

5.2 Analysis of Questionnaire Survey 2022 (First Survey)

5.2.1 Data Reliability Verification

Cronbach's alpha was calculated to measure data reliability. Cronbach's alpha coefficients were calculated using Bell Curve for Excel (Social Survey Research Information Co., Ltd.). In general, a Cronbach's alpha coefficient is considered consistent if it is greater than 80%.

The Cronbach's alpha coefficient for the 50 questions in this questionnaire was 96.73%. Therefore, it can be inferred that the questionnaire responses are consistent and reliable.

5.2.2 Latent Variable Definition

Covariance structure analysis was performed to test the hypothetical model. In the covariance structure analysis, the latent variables of the hypothetical model shown in Fig. 1 were defined by assigning the questionnaire survey items as observed variables. This definition of latent variables was also applied to the analysis of the questionnaire data conducted in 2022 and 2023.

Table 3 Occupation of respondents

	Occupation											
	Doctor or medical professional		Company employee (contract or temporary staff)		Company employee (full-time)		Manager or executive		Civil servant (excluding teacher or staff)		Total amount	
year	2022	2023	2022	2023	2022	2023	2022	2023	2022	2023	*2022*	*2023*
Type of industry												
Service	0	0	2	8	21	36	1	1	0	0	24	45
Media and advertising	0	0	1	0	1	1	1	1	0	0	3	2
Medical and welfare	0	13	1	3	8	19	0	0	1	0	13	35
Transportation	3	0	4	3	9	8	0	0	1	0	14	11
Education or schoolwork	0	0	2	2	6	7	0	0	2	3	10	12
Finance, securities, and insurance	0	0	1	4	6	14	0	0	0	0	7	18
Construction	0	0	0	0	15	25	2	1	0	0	17	26
Publishing and printing	0	0	0	0	3	7	0	0	0	0	3	7
Trading, wholesale, and retail	0	0	3	3	21	26	2	1	0	0	26	30
Telecommunications	0	0	6	2	15	24	0	0	0	0	21	26
Manufacturing	0	0	5	13	49	61	1	1	0	0	55	75
Research and think tanks	0	0	0	0	1	1	0	0	0	0	1	1
Electricity, gas, and water supply	0	0	1	2	1	4	0	0	0	0	2	6
Agriculture, forestry, fishing, and mining	0	0	0	0	3	1	0	0	0	0	3	1
Nonprofit organization	0	0	2	3	4	3	0	0	9	3	15	9
Real estate	0	0	1	1	8	9	3	2	0	1	12	13
Other	0	0	8	0	16	0	2	0	3	0	29	0
Total amount	3	13	37	44	187	246	12	7	16	7	255	317

The latent variable [L1:Concern] was defined by the following three observed variables: [M17: I can use reports on investigations into causes of failure and measures to prevent recurrence of failure in my work]; [M23: I think I can learn from reports on activities of my organization, such as analysis of causes of failure and planning of measures to prevent recurrence of failure]; and [M24: I think reports on activities of my organization, such as analysis of causes of failure and planning of measures to prevent recurrence of failure, contain information that may be relevant to me].

The Cronbach's alpha coefficient for the latent variable [L1: Concern] was 75.14%, which we considered acceptable.

The latent variable [L2: Computer-Based Repository] was defined by the following three observed variables: [M37: My organization uses computers to search for information on failure prevention measures, etc.]; [M38: My organization uses computers to store information on failure prevention measures, etc.]; and [M39: My organization uses computers to share information on failure prevention measures, etc.]

Cronbach's alpha for the resident variable [L2: Computer-based repository] is also 87.05%, which is above 80%; therefore, we consider it consistent.

The latent variable [L3: Record] was defined by the following three observation variables: [M31: In my organization (company), the way to prevent failure is specified by rules or documents]; [M32: In my organization (company), a manual to prevent failure is in place]; and [M33: In my organization (company), the way to prevent failure is specified or directed by business partners.]

The Cronbach's alpha coefficient for the latent variable [L3: Record] was 72.61%, which we considered acceptable.

The latent variable [L4: Human memory] was defined by the following three observed variables: [M34: Members of my organization (company) (supervisors, subordinates, colleagues) remember how to prevent failures]; [M35: Members of my organization (company) (supervisors, subordinates, colleagues) learn how to prevent failures]; and [M36: Members of my organization (company) (supervisors, subordinates, colleagues) know that there are ways and rules to prevent failures].

The Cronbach's alpha coefficient for the latent variable [L4: Human memory] was 75.51%, which we considered acceptable.

The latent variable [L5: Organizational memory] was defined by the following three observed variables: [M28: My organization (company) has accumulated measures to prevent recurrence of failure]; [M29: My organization (company) has the know-how to prevent recurrence of failure]; [M30: My organization (company) is able to elicit failure prevention measures through conversations, meetings, documents, etc.]; and [M31: I am able to draw out failure prevention measures through conversations, meetings, documents, etc..]

The Cronbach's alpha for the latent variable [L5: Organizational memory] was 81.47%, which was above 80%; therefore, it may be consistent.

5.2.3 Data Analysis for Hypothesis Testing of Questionnaire Survey 2022

Covariance structure analysis was performed using IBM SPSS AMOS28, software for statistical analysis, to test the hypothetical model.

Figure 4 shows the results of the covariance structure analysis of the hypothetical model.

The comparative fit index (CFI) was 0.965. Taking a value between 0 and 1, the closer CFI is to 1, the better the fit. A model with a value of 0.95 is often considered good. Therefore, we considered our hypothetical model a good. The root mean square error of approximation (RMSEA) was 0.059. In general, the RMSEA is considered a good fit if it is less than 0.05, a poor fit if it is greater than 0.10, and a gray zone if it is greater than 0.05 but less than 0.10. were considered a gray zone. Our hypothetical model was in the gray zone but with an acceptable margin of error. Thus, our hypothetical model was within the acceptable range, although it cannot be considered a good fit.

5.3 Analysis of Questionnaire Survey 2023 (Second Survey)

5.3.1 Data Reliability Verification

The Cronbach's alpha coefficient for the 50 questions in the questionnaire was 97.09%. Therefore, it can be inferred that the questionnaire responses were consistent and reliable.

Similarly, the Cronbach's alpha coefficient for the latent variable [L1: Concern] was 77.87%, which is considered acceptable. The Cronbach's alpha coefficient for the latent variable [L2: Computer-based repository] was also consistent at 88.02%, which is above 80%. The Cronbach's alpha coefficient of the latent variable [L3: Record] was 73.30%, and that of the latent variable [L4: Human memory] was 78.90%, which is considered acceptable. The Cronbach's alpha for the latent variable [L5: Organizational memory] was 85.11%, which may be consistent.

Covariance structure analysis was performed using IBM SPSS AMOS29, software for statistical analysis, to test the hypothetical model.

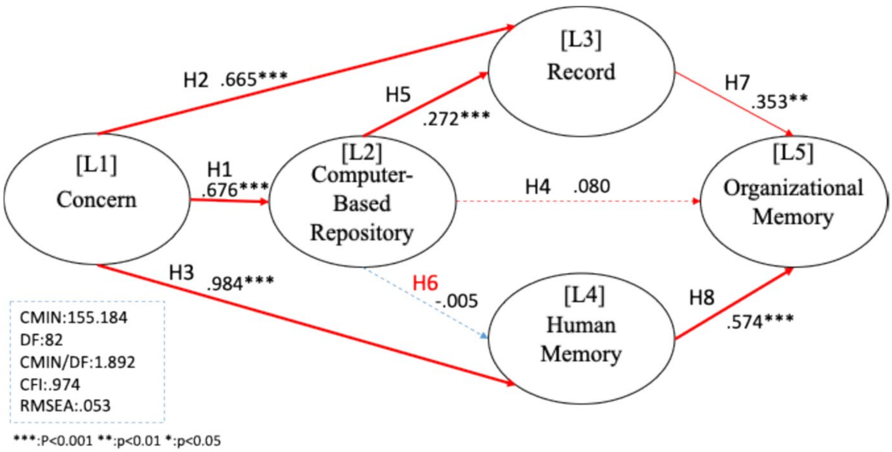

Fig. 4 Results of structural equation modeling of questionnaire survey 2022

Figure 5 shows the results of the covariance structure analysis of the hypothetical model.

Based on the results of the covariance structure analysis, we evaluated the modified hypothetical model with a CFI of 0.974. The CFI was 0.974, indicating that the hypothetical model is a good model. The RMSEA was 0.053, which was in the gray zone but within the acceptable error range. Thus, this hypothetical model cannot be considered a good fit, although it is within the acceptable range.

6 Results and Discussion

6.1 Hypothesis Verification

6.1.1 Verification of Questionnaire Survey 2022(First Survey)

The results of the 2022 survey data analysis are discussed and the hypotheses tested.

For H1, the correlation coefficient for [L1: Concern] → [L2: Computer-based repository] was 0.593, significant at the 0.1% level. Therefore, H1 is supported. For H2, the correlation coefficient for [L1: Concern] → [L3: Record] was 0.690, significant at the 0.1% level. Thus, H2 is supported. For H3, the correlation coefficient for [L1: Concern] → [L4: Human memory] was 0.894, significant at the 0.1% level. Therefore, H3 is supported. For H4, the correlation coefficient for [L2: Computer-based repository] → [L5: Organizational memory] was 0.127, significant at the 5% level. Therefore, H4 could be supported. For H5, the correlation coefficient for [L2: Computer-based repository] → [L3: Record record] was 0.257, significant at the 1% level. Therefore, H5 could be supported. For H6, the correlation coefficient for [L2: Computer-based repository] → [L4: Human memory] was 0.066, and not significant. Thus, there is little chance that H6 is supported. For H7, the correlation coefficient for [L3: Record] → [L5: Organizational memory] was 0.279, significant at the 1%

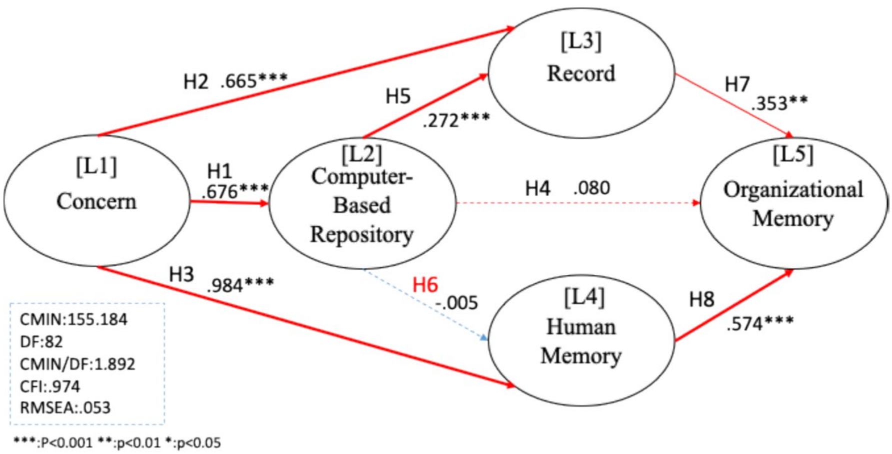

Fig. 5 Results of structural equation modeling of questionnaire survey 2023

Table 4 Hypothesis testing comparison of 2022 and 2023

Path						Support significance correlation			Support significance significance		
Questionnaire Survey (Year)						1st (2022)			2nd (2023)		
H1	L1	Concern	→	L2	Computer-based repository	.593	***	Yes	.676	***	Yes
H2	L1	Concern	→	L3	Record	.690	***	Yes	.665	***	Yes
H3	L1	Concern	→	L4	Human memory	.894	***	Yes	.984	***	Yes
H4	L2	Computer-based repository	→	L5	Organizational memory	.127	*	Yes	.080		No
H5	L2	Computer-based repository	→	L3	Record	.254	**	Yes	.272	***	Yes
H6	L2	Computer-based repository	→	L4	Human memory	.066		No	−.005		No
H7	L3	Record	→	L5	Organizational memory	.279	**	Yes	.353	**	Yes
H8	L4	Human memory	→	L5	Organizational memory	.691	***	Yes	.574	***	Yes

level. Therefore, H7 could be supported. For H8, the correlation coefficient for [L4: Human memory] → [L5: Organizational memory] was 0.691, significant at the 0.1% level. Therefore, H8 is supported.

6.1.2 Verification of Questionnaire Survey 2023 (Second Survey)

The results of the 2023 survey data analysis are discussed and the hypotheses tested.

The correlation coefficient for H1 was 0.676, significant at the 0.1% level. The correlation coefficient for H2 was 0.665, significant at the 0.1% level. The correlation coefficient for H3 was 0.984, significant at the 0.1% level. Hence, H1–H3 are supported. The correlation coefficient for H4 was 0.080, and not significant. Hence, H4 is not supported. The correlation coefficient for H5 was 0.272, significant at the 0.1% level. Therefore, H5 is supported. The correlation coefficient for H6 was − 0.005, and not significant. Therefore, there is no possibility that H6 is supported. H7 had a correlation coefficient of 0.353, significant at the 1% level. Therefore, H7 is unlikely to be supported. The correlation coefficient for H8 was 0.574, significant at the 0.1% level. Therefore, H8 is supported.

6.2 Comparison Analysis between the Questionnaire Surveys in 2022 and 2023

Table 4 summarizes the results of the analysis of the two surveys conducted at different times of the year and with different survey targets, that is, the surveys conducted in 2022 and 2023.

Comparing the two questionnaires conducted at different times and with different survey targets, that is, the questionnaires conducted in September 2022 and March 2023, the results of the analysis were almost the same, except for H4, for which the results of the 2022 questionnaire analysis had a correlation coefficient of 0.127, significant at the 5% level, while the results of the 2023 questionnaire analysis were not significant at the 5% level, with a correlation coefficient of 0.127. The 2023 questionnaire was not significant, with a correlation coefficient of 0.08; however, because both questionnaires showed low correlation coefficients (Table 4), it is difficult to say that there is necessarily a correlation between the two questionnaires. Overall, it is safe to assume that the hypothetical model has been verified, because the results of the two questionnaire surveys are similar.

6.3 Findings

H1 was tested using data from the two surveys. Similarly, H2 and H3 were also tested. It can be inferred that matters of interest to organizational members, such as "wanting to prevent failures" and "not wanting to be involved in failures," not only promote the utilization of the knowledge sharing infrastructure by organizational members, but also tend to be kept as records and remembered by people. This is a further test of Monty et al.'s [33] study of human memory, in which they argue that memory is enhanced by the motivation of self-involvement in the subject matter, and at the same time suggest that the same holds for knowledge-sharing infrastructure and recording activities.

With regard to H8, since organizations are composed of people, it is logically explicable that organizational memory is strengthened by human memory. Taken together with H3, we confirmed that, if the task is of interest, human memory is prompted, and furthermore, results in organizational memory. However, H6 is not supported. In other words, it was shown that utilization of knowledge-sharing infrastructure does not necessarily facilitate human memory. Sparrow et al. [20] and Wegner and Ward [21] argue for digital amnesia, and Greenfield [22] discusses the possibility of Internet-related technologies eroding human memory. Nagayoshi and Nakamura [23] state that computer-based knowledge-sharing systems may impair personal memory. The present study supports these prior studies.

H4 while the results of the 2022 questionnaire analysis showed a correlation coefficient of 0.127, significant at the 5% level, those of the 2023 questionnaire showed a correlation coefficient of 0.08, and not significant. However, both questionnaires had low correlation coefficients, and thus, it is difficult to say that they are correlated. Therefore, the results indicate that organizational memory is not necessarily strengthened when knowledge-sharing infrastructure is utilized. Meanwhile, H5 and H7 were supported. This suggests that recording activities are facilitated through the use of computer-based knowledge-sharing infrastructure, which facilitates knowledge accumulation and retrieval [11]. Thus, it is clear that the use of computer-based knowledge-sharing infrastructure does not directly contribute to organizational memory, but does so indirectly through the promotion of recording activities by the use of computer-based knowledge-sharing infrastructure.

Computer-based knowledge repositories may indirectly enhance organizational memory by intervening in the act of recording. Exploring the interface between cognitive psychology and organizational theory, Cohen [16] focuses on the distinction between procedural memory and declarative memory, Cohen and Bacdayan [17] subsequently show through laboratory experiments that organizational routines emerge and that personal memories of elements of organizational routines are stored as procedural memories. In other words, the organizational routine is a system whose elements are personal memories, but personal memories, which are elements of this system, are stored as procedural memories. Moreover, according to Simon [15] and

Cook and Yanow [34], even if the component individual memories of this system are replaced, persistence survives in the patterns of relationships among the elements. The persistence of organizational routines is the key to understanding organizational memory and organizational learning, and it may be that organizations are merely containers of organizational routines [18]. Therefore, we do not interpret the results to mean that a computer-based knowledge repository enhances organizational memory, but rather that the organization remembers the information through organizational routines that enhance the later stages of recording by utilizing the computer-based knowledge repository.

7 Conclusion

Through a statistical analysis of quantitative data collected over 2 years through a questionnaire targeting employees working in Japanese companies, this study reveals that computer-based knowledge-sharing infrastructure does not directly enhance organizational memory but rather enhances organizational memory by facilitating the act of recording. This study also revealed that the use of computer-based knowledge sharing infrastructure, recording, and human memory are facilitated when organizational members are interested in such matters as wanting to prevent failure and not wanting to be a participant in failure. Furthermore, the results suggest that while enhanced human memory enhances organizational memory, the use of computer-based knowledge-sharing infrastructure does not necessarily promote human memory.

In the previous studies [25–27], the relationship between the use of computer-based knowledge-sharing infrastructure and organizational memory was discussed in case studies of the company that successfully implemented organizational learning from failure; however, the relationship could not be generalized. This study allows the possibility of generalization. This study also suggests that utilizing computer-based knowledge-sharing infrastructure does not necessarily enhance organizational memory but that it is crucial to utilize it as an organizational routine. This finding has important practical implications, because it identifies how companies can overcome organizational learning from failure. These implications complement the traditional assertion of the importance of changing an enduring organizational culture in organizations [35] for digital transformation.

This study analyzed data collected through an Internet questionnaire. However, we could not rule out the possibility we might have had some cognitive bias in creating the questionnaire items. We also could not rule out the possibility that the respondents provided normative answers without relying on their own experiences and perceptions. Furthermore, the collected survey data contained many fraudulent responses, such as straight-line responses. Although great care was taken to eliminate fraudulent responses, not all were necessarily removed. In addition, we could not rule out the possibility that the elimination of fraudulent responses might have reduced the sample size used for the data analysis, thereby decreasing the reliability of the data sample.

Future research should follow up on the findings of this study using sufficiently reliable qualitative and quantitative data. In addition, this study was based on a questionnaire survey of employees working in unspecified Japanese companies. A comparative analysis of these results with those collected in companies that have successfully implemented organizational learning from failure should be conducted to determine why these case companies have been able to successfully implement organizational learning from failure. It is also necessary to investigate why these companies could successfully implement organizational learning from failure by comparing the results with questionnaire results collected from companies that have successfully implemented organizational learning from failure.

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Data Availability The data that support the findings of this study are not publicly available due to confidentiality agreements with participating organizations and the need to protect respondents' anonymity. Data may be available from the corresponding author upon reasonable request, subject to ethical and contractual restrictions.

Declarations

Conflict of interest The authors have no conflict of interest directly relevant to the content of this article.

Ethical Considerations This study complied with the ethical standards of research involving human participants. Participation was voluntary, and respondents were informed about the purpose of the study and their right to withdraw at any time.The survey was conducted anonymously, and no personally identifiable information was collected. All data were analyzed in aggregate form.

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