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Design and Validation of a Self-Directed Learning Management Model in Organizational Training at Bank Sepah

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ABSTRACT

Due to their inherently competitive nature in attracting customers and financial resources, as well as their continual exposure to unpredictable fluctuations in both domestic and international economies, banks face a constant need to enhance their knowledge competencies. One of the key approaches in organizational learning management is the adoption of self-directed learning. The present study was conducted with the aim of designing and validating a self-directed learning management model for organizational training programs at Bank Sepah. This study is applied in its objective and employs a mixed-methods design in terms of methodology. In the qualitative phase, data were analyzed using the grounded theory approach. The required data were collected through semi-structured and in-depth interviews and analyzed based on a coding process. Sampling in this phase was theoretical, utilizing purposive and snowball techniques. In total, open interviews were conducted with 12 banking managers and academic experts. Through open coding, a set of initial themes was extracted and then categorized into conceptual components. Preliminary analysis of the interviews led to the identification of 158 initial codes. In the second stage of coding, after examining the initial codes and analyzing their similarities and differences, 112 codes were grouped into 20 categories, which were organized under the systematic paradigm model, including causal conditions, contextual conditions, strategies, intervening conditions, and outcomes. Using this approach, all dimensions and components influencing self-directed learning were comprehensively covered. In the quantitative phase, the number of experts was 23, and sampling was conducted using the convenience sampling method. The statistical population consisted of managers and employees of the bank, through whom model validation and survey data collection were carried out. To achieve the research objectives and answer the study questions, the factors identified in the qualitative phase were used as inputs for interpretive structural modeling (ISM), through which the hierarchical levels were determined. Accordingly, the "individual capabilities" index was identified as the foundational and core element of the self-directed learning model in organizational training at Bank Sepah.

Keywords: Self-directed learning, Bank Sepah, learning culture implementation, individual capabilities, grounded theory analysis, interpretive structural modeling (ISM).

Introduction

In today's rapidly evolving organizational landscape, self-directed learning (SDL) has emerged as a foundational approach to sustaining continuous development and adaptability in both educational and professional contexts. As organizations face complex technological transformations, global competition, and changing workforce dynamics, the ability of employees to manage their own learning has become an essential competency for maintaining long-term performance and innovation [1, 2]. The modern workplace, characterized by decentralization of knowledge and rapid information flow, demands that individuals take greater responsibility for identifying learning needs, setting goals, and evaluating their progress [3]. This paradigm shift from teacher-centered to learner-centered education underlines the necessity of cultivating SDL skills, which empower individuals to remain agile and autonomous in achieving personal and organizational growth [4].

The conceptual roots of self-directed learning can be traced to adult learning theories and humanistic psychology. Knowles's (2018) andragogical model conceptualized SDL as an intentional and proactive process in which learners diagnose their learning needs, formulate goals, identify resources, and evaluate outcomes [4]. This notion aligns with constructivist perspectives emphasizing active engagement, self-reflection, and knowledge construction [5]. Empirical evidence has consistently demonstrated that SDL contributes to deeper cognitive engagement, higher academic achievement, and better adaptation to new professional challenges [2, 6]. In this regard, Williamson (2022) further contributed to the operationalization of SDL by developing self-assessment scales, providing measurable criteria to evaluate learners' autonomy, motivation, and self-monitoring [3]. Recent developments in psychology and education have linked SDL with several cognitive and affective constructs. Studies show that self-regulation, critical thinking, and emotional creativity are strong predictors of self-directed learning outcomes [7, 8]. For instance, learners with high readiness for SDL exhibit superior problem-solving and metacognitive abilities, leading to improved academic performance and career adaptability [8]. The development of these competencies depends not only on individual factors such as motivation and self-efficacy but also on contextual elements such as supportive learning environments and organizational culture [9, 10].

In organizational learning contexts, SDL is integral to fostering innovation, adaptability, and resilience. Moghadam Zadeh et al. (2018) emphasized that self-directed learners contribute to the enhancement of organizational learning processes by engaging in continuous self-improvement, knowledge sharing, and reflective practice [11]. Similarly, Hasanvandi and Ramadan (2019) observed that organizations promoting SDL tend to develop stronger intellectual capital and achieve more sustainable performance outcomes [10]. These findings align with the broader perspective of lifelong learning and emphasize the value of individual autonomy and learning motivation in the digital era [12]. The emergence of information and communication technologies (ICT) has further revolutionized SDL practices in educational and professional environments. Seng Chee et al. (2021) highlighted the importance of ICT-based self-directed learning frameworks, noting that digital tools enable learners to plan, monitor, and evaluate their learning with unprecedented flexibility and personalization [13]. Similarly, Macintyre et al. (2021) argued that digital transformation in education management has expanded the boundaries of SDL by promoting interactive, networked, and data-driven learning ecosystems [14]. This integration of technology into learning environments allows for adaptive feedback systems and real-time monitoring, enhancing the learner's sense of agency and accountability [15].

From a psychological perspective, recent studies have established strong connections between SDL and psychological capital—defined as a composite of self-efficacy, optimism, hope, and resilience. Research conducted by Xiu-Juan et al. (2024) and Yang (2024) demonstrated that psychological capital mediates the relationship between perceived stress and SDL ability among nursing students, suggesting that emotional and psychological resources are critical for sustaining self-directed behavior under stress [15, 16]. Similarly, Talebzadeh Shushtari and Boyeri (2024) found that emotional creativity and critical thinking tendencies foster achievement motivation, which, in turn, promotes higher SDL readiness [7]. These findings highlight the multidimensional nature of SDL as an interaction between cognitive, affective, and contextual factors.

Grounded theory and qualitative inquiry have also played a central role in deepening the understanding of SDL processes and their underlying mechanisms. Strauss and Corbin (2015) emphasized the importance of systematic coding and theoretical sampling in revealing the dynamic and emergent nature of learning behaviors [17]. Kersoul (2023) extended this approach by integrating narrative and phenomenological techniques to explore the lived experiences of self-directed learners in diverse educational settings [18]. The combination of grounded theory with interpretive structural modeling (ISM) has been especially useful in designing conceptual models that reveal causal relationships among SDL components [19, 20].

ISM as a methodological framework provides a systematic and visual representation of hierarchical relationships among factors affecting SDL in organizations [21]. This approach enables the identification of driving and dependent variables, facilitating strategic interventions in educational management systems [19, 22]. In line with this, ISM has been widely used to structure complex decision-making processes, such as supplier selection, renewable energy adoption, and logistics outsourcing, which share conceptual parallels with SDL in terms of interrelated behavioral and environmental variables [21, 22]. By adapting ISM to the domain of organizational learning, researchers can reveal the multi-level dynamics that govern the self-directed learning process in institutional contexts.

Cultural and institutional factors also play a pivotal role in shaping SDL outcomes. Studies conducted in Iranian academic and organizational environments have shown that sociocultural expectations, hierarchical structures, and managerial support significantly influence learners' autonomy and motivation [9, 23]. In particular, participatory learning models that encourage active collaboration and shared decision-making have been associated with improved self-regulation and academic achievement [23]. Similarly, the establishment of a learning culture within organizations—supported by information technology infrastructure and knowledge-sharing systems—creates fertile ground for the flourishing of SDL practices [9, 10].

Moreover, recent theoretical discussions emphasize the synergy between self-directed learning and experiential learning theories. Experiential learning, as described by Fisher et al. (2019), provides learners with opportunities to connect theoretical knowledge with practical application through reflection, experimentation, and feedback [24]. When embedded within self-directed frameworks, experiential learning enhances metacognitive awareness and reinforces learners' intrinsic motivation to engage in continuous improvement. Similarly, Pittayarat Yamprayoon and Jermtaisong (2020) demonstrated that collaborative and communicative learning methods stimulate self-direction by fostering peer interaction and self-evaluation in real-world problem-solving contexts [25].

At the organizational level, the connection between SDL and job performance has been substantiated through various empirical investigations. Ghasemzadeh Alishahi et al. (2020) found that learning-oriented work environments significantly enhance employees' learning capacity, which in turn contributes to higher performance outcomes and competitive advantage [9]. Likewise, Grover and Miller (2018) observed that self-directed learners exhibit greater adaptability, innovation, and resilience, which are essential for maintaining organizational competitiveness in volatile markets [12]. In this regard, SDL not only benefits individual career development but also serves as a strategic driver for organizational learning and transformation [10, 11]. From a global perspective, recent studies highlight the contextual variability of SDL implementation. For instance, Lounsbury et al. (2024) examined the construct validity of SDL as a personality trait across diverse populations, revealing cultural differences in learners' autonomy and initiative [1]. Similarly, research in developing regions underscores the importance of socio-economic support, managerial encouragement, and structural reforms in embedding SDL within institutional frameworks [5, 21]. These contextual insights provide valuable guidance for tailoring SDL models to specific educational and organizational environments, ensuring their relevance and sustainability. In synthesis, self-directed learning represents a multidimensional construct encompassing psychological readiness, technological facilitation, cultural context, and organizational structure. The integration of grounded theory and interpretive structural modeling offers a robust methodological foundation for identifying the interdependencies among these components [17, 19]. The aim of this study is to design and validate a self-directed learning management model in organizational training at Bank Sepah, integrating qualitative grounded theory and interpretive structural modeling approaches.

Methodology

From a methodological perspective, the present study is a mixed-methods research that is applied in purpose and descriptive–survey in nature and method. In this design, qualitative data were first collected and analyzed, followed by the collection and examination of quantitative data. Semi-structured interviews were used to gather qualitative data, while quantitative data were collected through a questionnaire.

The qualitative data analysis was based on the grounded theory approach, employing Strauss and Corbin's coding method. Grounded theory serves as a tool for developing information categories (open coding), establishing relationships among these categories (axial coding), and constructing a coherent narrative that links them together (selective coding), ultimately leading to the formulation of a set of theoretical propositions.

In the quantitative phase, the interpretive structural modeling (ISM) method was employed to analyze the data and determine the hierarchical levels of the model's dimensions. ISM is a managerial and interactive tool that organizes and directs the complex relationships among components, transforming unclear and ambiguous mental models of a system into clear and comprehensible ones. This approach is based on an interactive learning process and utilizes group decision-making and judgment to uncover the relationships among components and their modes of interaction. ISM is widely used in various organizational, managerial, and industrial contexts, and due to its structural simplicity and user comprehensibility, it is considered an effective tool for addressing complex issues through systematic and logical thinking.

In the qualitative phase of the study, purposive sampling was employed to select participants, while snowball sampling was used to identify and recruit key informants. Interviews were conducted with 12 subject-matter experts to collect their insights regarding the research components. The interview process was designed in such a way that the data were coded and analyzed after each session, and the identified components, upon expert verification, were followed up in subsequent interviews. The sample size was determined using the theoretical sampling method, and data collection continued until theoretical saturation was achieved. By the twelfth interview, the data had become repetitive and no new concepts were identified, thereby confirming the adequacy of the sample. In the research literature domain, all upper-level documents were considered part of the documentary population, while in the strategic domain, all related managers and experts constituted the statistical population. Table 1 presents the demographic characteristics of the respondents.

Table 1

Demographic Characteristics of Respondents

Variable	Status	Frequency	Percentage
Employment Status	Academic Activities	3	25%
	Business	6	50%
	Both Fields	3	25%
Field of Study	Educational Management	5	42%
	Banking Sciences	3	25%
	Public Administration	2	16%
	Educational Sciences	2	16%
Education Level	Master's Degree	3	25%
	Ph.D.	9	75%

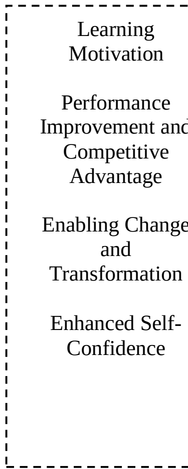
In the validation phase, given that data analysis was conducted using interpretive structural modeling—which relies on expert judgment—a sample size between 10 and 16 participants is generally considered sufficient for analysis. Accordingly, in the validation stage of this research, 23 experts in the field of educational management within the banking sector, who were knowledgeable in this domain and accessible to the researchers, were selected as the sample through convenience sampling.

Findings and Results

In this study, data analysis was conducted using the systematic approach of Strauss and Corbin's grounded theory, which involves three main stages: open coding, axial coding, and selective coding, all based on the constant comparative method. In the axial coding stage, the relationships among the categories were identified under the titles of causal conditions, core phenomenon, strategies, contextual conditions, intervening conditions, and consequences.

Figure 1

The Paradigm Model of the Study



Through analysis of the interviews conducted in the first phase, 158 initial codes were extracted. In the second coding phase, by carefully reviewing the initial codes and identifying their similarities and differences, some codes were removed or merged, and finally, similar codes were organized into broader categories. In total, 112 initial codes were classified into 20 categories, each falling under one of the subcategories of the systematic paradigm model (causal conditions, contextual conditions, strategies, intervening conditions, and consequences). According to the components of the study's paradigm model (Figure 1), all dimensions and factors influencing self-directed learning were comprehensively addressed in this process.

To assess the reliability of the measurement model, the Composite Reliability (CR) index was used. A CR value greater than 0.7 for each construct indicates desirable internal consistency of the measurement models. The related results are presented in the following table.

Table 2

Results of Cronbach's Alpha and Composite Reliability for Latent Variables

Latent Variables	Abbreviation	Cronbach's Alpha (α > 0.7)	Composite Reliability (CR > 0.7)
Causal Conditions	A	0.795	0.841
Contextual Conditions	B	0.707	0.799
Intervening Conditions	C	0.788	0.843
Influencing Indicators	D	0.854	0.930
Strategies	E	0.844	0.882
Consequences	F	0.742	0.763

Since Cronbach's alpha and composite reliability values equal to or higher than 0.7 are considered acceptable, and as indicated in the table above, these indices demonstrated appropriate values for the latent variables, the reliability of the study can be confirmed.

In this study, to validate the self-directed learning management model in organizational training at Bank Sepah, the Interpretive Structural Modeling (ISM) method was used, following the procedure proposed by Kannan et al. (2009) and Sindu et al. (2016).

Step 1: Identification of Research Indicators

At this stage, and based on the results of the qualitative phase and the paradigm model presented in Figure 1, 20 indicators were selected for structuring and designing the self-directed learning model in organizational training at Bank Sepah.

Table 3

Indicators of the Self-Directed Learning Model in Organizational Training at Bank Sepah

No.	Indicator	Indicator Code
1	Repetition and Review Strategies	C1
2	Elaboration and Semantic Expansion Strategies	C2
3	Organizational Strategies	C3
4	Creative Inquiry	C4
5	Environmental Dynamism	C5
6	Individual Capabilities	C6
7	Organizational Hierarchy	C7
8	Top Management Support	C8
9	Individual Barriers	C9
10	Establishment of Learning Culture	C10
11	Information Technology Infrastructure	C11
12	Knowledge Sharing and Development	C12
13	Experiential Learning	C13
14	Emphasis on Implicit Learning	C14
15	Reward and Evaluation Systems	C15
16	Learning Motivation	C16
17	Performance Improvement and Competitive Advantage	C17
18	Enabling Change and Transformation	C18
19	Enhanced Self-Confidence	C19
20	Improvement of Self-Directed Learning	C20

Step 2: Data Collection and Formation of the Structural Self-Interaction Matrix (SSIM)

At this stage, experts evaluated the research indicators through pairwise comparisons, determining the relationships among them using the following symbols:

V: One-way relationship from *i* to *j*

A: One-way relationship from *j* to *i*

X: Two-way relationship between *i* and *j*

O: No relationship between *i* and *j*

Accordingly, based on these symbols, experts identified the relationships among indicators in the questionnaire, and the results are presented in Table 4.

Table 4

Structural Self-Interaction Matrix (SSIM)

J	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
I	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
C1	-	A	V	O	A	A	V	O	A	X	O	O	A	V	O	V	O	A	A	O
C2	-	-	O	A	V	O	V	X	O	O	A	V	O	O	V	V	V	A	O	O
C3	-	-	-	A	A	A	V	X	V	O	V	V	V	O	A	A	O	O	V	V
C4	-	-	-	-	V	A	V	A	O	O	V	V	X	O	A	V	O	O	V	V
C5	-	-	-	-	-	A	V	X	V	X	X	V	V	A	A	V	O	A	A	O
C6	-	-	-	-	-	-	V	V	O	V	A	V	V	O	V	V	V	V	O	V
C7	-	-	-	-	-	-	-	A	X	X	X	O	V	O	A	X	V	X	O	O
C8	-	-	-	-	-	-	-	-	V	V	A	A	O	O	O	V	O	A	O	V
C9	-	-	-	-	-	-	-	-	-	O	A	O	A	O	A	A	O	A	A	O
C10	-	-	-	-	-	-	-	-	-	-	O	A	O	A	V	V	O	A	O	X
C11	-	-	-	-	-	-	-	-	-	-	-	V	V	V	V	V	V	V	V	V
C12	-	-	-	-	-	-	-	-	-	-	-	-	O	V	A	O	A	A	V	O
C13	-	-	-	-	-	-	-	-	-	-	-	-	-	A	A	A	A	X	O	O
C14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	O	V	V	O	O	O
C15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	V	O	A	O	O
C16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	V	V	O	V
C17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	A	A	O
C18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	A	V
C19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	V
C20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Step 3: Formation of the Initial Reachability Matrix

The initial reachability matrix is a 0–1 structural self-interaction matrix obtained by converting the symbols V, A, X, and O according to the following rules:

- If the relationship between indicators is V, then (i, j) = 1 and (j, i) = 0.
- If the relationship is A, then (i, j) = 0 and (j, i) = 1.
- If the relationship is X, then both (i, j) and (j, i) = 1.
- If the relationship is O, then both (i, j) and (j, i) = 0.
- Moreover, for i = j, the value 1 is assigned to the diagonal entries of the matrix. Following this procedure, the initial reachability matrix of the study is presented in Table 5.

Table 5

Initial Reachability Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	1	0	1	0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0
C2	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	0	0
C3	0	0	1	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	1	1
C4	0	1	1	1	1	0	1	0	0	0	1	1	1	0	0	1	0	0	1	1
C5	1	0	1	0	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0
C6	1	0	1	1	1	1	1	1	0	1	0	1	1	0	1	1	1	1	0	1
C7	0	0	0	0	0	0	1	0	1	1	1	0	1	0	0	1	1	1	0	0
C8	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0	1	0	0	0	1
C9	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
C10	1	0	0	0	1	0	1	0	0	1	0	0	0	0	1	1	0	0	0	1
C11	0	1	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
C12	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	1	0
C13	1	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0
C14	0	0	0	0	1	0	0	0	0	1	0	0	1	1	0	1	1	0	0	0
C15	0	0	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0	0	0	0
C16	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	1	1	1	0	1
C17	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0
C18	1	1	0	0	1	0	1	1	1	1	0	1	1	0	1	0	1	1	0	1
C19	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1
C20	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1

Step Four: Formation of the Final Reachability Matrix

To obtain the final reachability matrix, transitivity among the relationships between indicators must be applied, and the initial reachability matrix must be adjusted accordingly. Transitivity means that if indicator *i* leads to indicator *j* and indicator *j* leads to indicator *k*, then indicator *i* also leads to indicator *k*.

The method for calculating the final reachability matrix is based on Euler's theorem. In this method, the adjacency matrix is first added to the identity matrix, and then this resulting matrix is raised to the power of *n* until no further changes occur in its elements. The following formulas illustrate how the final reachability matrix is derived from the adjacency matrix:

1. $A + I$
2. $M = (A + I)^n$

In these formulas, matrix **A** represents the initial reachability matrix, **I** represents the identity matrix, and **M** represents the final reachability matrix. The matrix exponentiation operation is performed according to Boolean algebra rules, meaning that $1 \times 1 = 1$ and $1 + 1 = 1$.

The results are presented in Table 6. In this table, the numbers marked with an asterisk (*) indicate the cells that were originally zero in the initial reachability matrix but changed to one after applying the transitivity adjustment.

Table 6

Final Reachability Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	Driving Power
C1	1	0	1	0	1*	0	1	1*	1*	1	1*	1*	1*	1	1*	1	1*	1*	1*	1*	17
C2	1	1	0	0	1	0	1	1	1*	1*	1*	1	1*	1*	1	1	1	1*	1*	1*	19
C3	1*	1*	1	1*	1*	1*	1	1	1	1*	1	1	1	1*	1*	1*	1*	1*	1	1	20
C4	1*	1	1	1	1	1*	1	1*	1*	1*	1	1	1	1*	1*	1	1*	1*	1	1	20
C5	1	1*	1	1*	1	1	1	1	1	1	1	1	1	1*	1*	1	1*	1*	1*	1*	20
C6	1	1*	1	1	1	1	1	1	1*	1	1*	1	1	1*	1	1	1	1	1*	1	20
C7	1*	1*	1*	1*	1*	1*	1	1*	1	1	1	1*	1	1*	1*	1	1	1	1*	1*	20
C8	1*	1	1	1	1	0	1	1	1	1	1*	1*	1*	0	1*	1	1*	1*	1*	1	18
C9	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	4

C10	1	0	1*	1*	1	0	1	1*	1*	1	1*	1*	1*	1*	1	1	1*	1*	0	1	17
C11	1*	1	1*	1*	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	20
C12	1*	1*	1*	1*	1*	0	1*	1	1*	1	0	1	1*	1	1*	1*	1*	1*	1	1*	18
C13	1	1*	1*	1	1*	0	1*	1*	1	1*	1*	1*	1	1*	1*	1*	1*	1	1*	1*	19
C14	1*	0	1*	1*	1	0	1*	1*	1*	1	1*	1*	1	1	1*	1	1	1*	0	1*	17
C15	1*	1*	1	1	1	0	1	1*	1	1	1*	1	1	0	1	1	1*	1*	1*	1*	18
C16	1*	1*	1	1*	1*	0	1	1*	1	1*	1*	1*	1	0	1*	1	1	1	1*	1	18
C17	1*	0	0	1*	0	0	0	1*	1*	1*	0	1	1	1*	0	0	1	1*	1*	0	11
C18	1	1	1*	0	1	0	1	1	1	1	1*	1	1	1*	1	1*	1	1	1*	1	18
C19	1	1*	1*	0	1	0	1*	1*	1	1*	1*	1*	1*	1*	1*	1*	1	1	1	1	18
C20	0	1*	0	0	1*	1*	1*	1*	1*	0	1	1*	1*	1*	1*	1*	1*	1*	1*	1	16
Dependency	19	15	18	15	18	7	19	19	20	19	18	19	20	17	18	19	20	20	17	18	

Step Five: Level Partitioning of the Indicators

In this stage, the final reachability matrix is partitioned into different levels. For each indicator, the input set and the output set are determined. The input set includes the indicator itself and all indicators that affect it (the count of 1s in each column), and the output set includes the indicator itself and the indicators that are affected by it (the count of 1s in each row).

Afterward, the list of intersection sets is prepared; this set includes the indicators that are present in both the input and output sets. Indicators whose output set and intersection set are exactly identical are placed at the highest level of the interpretive structural model hierarchy. To determine the components of the next level, the higher-level indicators are removed from the calculations, and the same procedure is repeated to determine the subsequent level.

Given the considerable volume of calculations, the final results of level partitioning of the indicators are presented in Table 7.

Table 7

Determination of Indicator Levels

Indicator	Output Set	Input Set	Intersection Set	Level
C9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,3,7,9,10,11,13,14,16,17,18	1,3,7,9,10,11,13,14,16,17,18	I
C13	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,2,3,4,5,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,2,3,4,5,7,8,9,10,11,12,13,14,15,16,17,18,19,20	I
C17	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,4,8,9,10,12,13,14,17,18,19	1,4,8,9,10,12,13,14,17,18,19	I
C18	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,2,3,5,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,2,3,5,7,8,9,10,11,12,13,14,15,16,17,18,19,20	II
C2	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,7,8,11,12,15,16,19,20	2,3,4,5,7,8,11,12,15,16,19,20	II
C5	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	II
C7	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	II
C8	2,3,4,5,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,7,8,11,12,15,16,19,20	II
C12	2,3,4,5,7,8,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,7,8,12,15,16,19,20	II
C16	2,3,4,5,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,4,5,7,8,11,12,15,16,19,20	II
C19	2,3,5,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,3,5,7,8,11,12,15,16,17,19,20	II
C20	2,5,6,7,8,11,12,15,16,19,20	2,3,4,5,6,7,8,11,12,15,16,19,20	2,5,6,7,8,11,12,15,16,19,20	III
C1	3,4,6,11	3,4,6,11	3,4,6,11	III
C3	3,4,6,11	3,4,6,11	3,4,6,11	III
C4	3,4,6,11	3,4,6,11	3,4,6,11	III
C10	3,11	3,4,6,11	3,11	III
C11	3,4,6,11	3,4,6,11	3,4,6,11	III
C14	3,4,11	3,4,6,11	3,4,11	III
C15	3,4,11	3,4,6,11	3,4,11	III
C6	3,4,6,11	3,4,6,11	3,4,6,11	IV

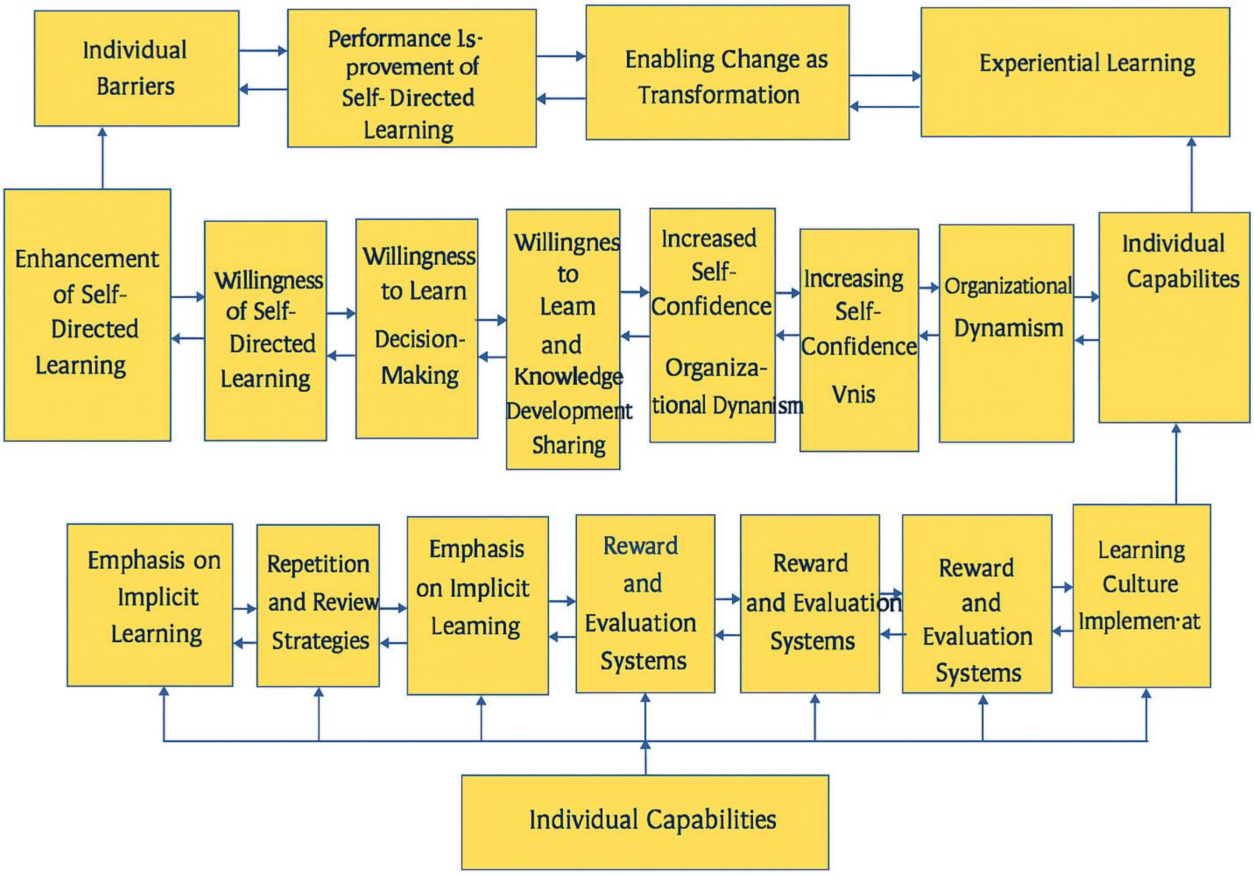
In view of Table 7, it is observed that the more precisely and comprehensively the lower-level indicators are realized, the easier and more attainable it becomes to achieve the higher-level indicators.

Step Six: Model Drawing

In this stage, based on the variable levels and the final reachability matrix, the ISM model is drawn. In other words, by combining the relationships among the indicators, a network diagram of their interactions is depicted. This model shows the hierarchy of the placement of factors relative to one another and the relationships among them, such that the higher-level indicators are influenced by their lower-level counterparts. In fact, the drawn model is a graphical representation of the tables computed in the previous steps. For this purpose, the indicators are first ordered from bottom to top according to their level. In the present study, the indicators are distributed across four levels, as shown in Figure 2.

Figure 2.

Structural Model of the Indicators of the Self-Directed Learning Model in Organizational Training at Bank Sepah



Based on Figure 2, the indicator “Individual Capabilities” is identified as the foundation and infrastructure of the indicators in the self-directed learning model for organizational training at Bank Sepah.

Step Seven: Importance-Determination Model

In this stage, the importance-determination model is calculated based on the driving power and the level of dependence of the indicators in the final reachability matrix. The importance of each indicator is obtained by subtracting its dependence from its driving power. The results of this analysis are presented in Table 8.

Table 8

Importance and Ranking of the Indicators of the Self-Directed Learning Model

Indicator	Driving Power	Dependence	Importance	Rank
Repetition and Review Strategies	17	19	-2	8
Elaboration and Semantic Expansion Strategies	19	15	4	3
Organizational Strategies	20	18	2	4
Creative Inquiry	20	15	5	2
Environmental Dynamism	20	18	2	4
Individual Capabilities	20	7	13	1
Organizational Hierarchy	20	19	1	5
Top Management Support	18	19	-1	7
Individual Barriers	4	20	-16	10
Establishment of Learning Culture	17	19	-2	8
Information Technology Infrastructure	20	18	2	4
Knowledge Sharing and Development	18	19	-1	7
Experiential Learning	19	20	-1	7
Emphasis on Implicit Learning	17	17	0	6
Reward and Evaluation Systems	18	18	0	6
Learning Motivation	18	19	-1	7
Performance Improvement and Competitive Advantage	11	20	-9	9
Enabling Change and Transformation	18	20	-2	8
Enhanced Self-Confidence	18	17	1	5
Improvement of Self-Directed Learning	16	18	-2	8

In view of Table 8, indicators with more positive importance values have better ranks, and conversely, indicators with more negative values have worse ranks. Therefore, the importance of the indicator “Individual Capabilities” is superior to that of the other indicators.

Discussion and Conclusion

The results of the present study, which aimed to design and validate a self-directed learning management model for organizational training in Bank Sepah, revealed a multidimensional and hierarchically structured model composed of twenty interrelated components. Through the use of grounded theory and interpretive structural modeling (ISM), the study identified “individual capabilities” as the foundational element influencing higher-level indicators such as learning culture establishment, technological infrastructure, experiential learning, motivation, and performance enhancement. This finding highlights the significance of human capital as the core driver of self-directed learning (SDL) within organizational settings. The emphasis on individual competencies aligns with the argument that self-direction in learning originates from personal attributes such as autonomy, self-efficacy, motivation, and reflective ability [1, 4]. Knowles’s adult learning theory proposed that self-directed learners actively identify learning needs and take responsibility for their development. The structural positioning of “individual capabilities” as the base in the model confirms that organizational learning effectiveness depends on empowering employees to regulate and sustain their own learning processes [11, 12].

The results further revealed that elements such as “organizational hierarchy,” “top management support,” and “information technology infrastructure” serve as key contextual and structural enablers of SDL. These components form the intermediate layers of the model and demonstrate how organizational systems and leadership commitment facilitate a culture of continuous learning. This aligns with studies emphasizing that SDL flourishes in supportive environments where managerial structures encourage autonomy and experimentation [9, 10]. The introduction of digital tools and ICT-based frameworks also plays an essential role in supporting SDL, as evidenced by the integration of technological infrastructure into the model [13, 14]. By fostering accessibility, feedback, and interaction, ICT enables learners to manage their educational progress independently and collaboratively. Consistent with the findings of Macintyre et al. (2021), digital platforms not only enhance self-paced learning but also promote reflective practices and knowledge sharing across organizational networks.

The study's findings further emphasize "knowledge sharing and development," "establishment of learning culture," and "reward and evaluation systems" as essential mediators connecting individual-level competencies to organizational performance outcomes. These mediating variables indicate that SDL is not solely an individual activity but also a social process embedded within organizational culture. This supports the perspective of Moghadam Zadeh et al. (2018), who demonstrated that the interplay between self-directed and organizational learning strengthens collective learning capacity and adaptability. Similarly, Hasanvandi and Ramadan (2019) found that organizations that encourage knowledge dissemination and learning motivation experience higher innovation and intellectual capital accumulation. The presence of a strong learning culture in Bank Sepah, as revealed by this study, thus ensures that individual learning behaviors translate into collective competence, reinforcing the organizational ecosystem of knowledge creation [9, 10].

An important aspect of the study concerns the hierarchical relationships identified among the SDL components. The interpretive structural model (ISM) arranged the components across four levels, with individual factors at the foundation and performance-related outcomes at the top. This structure mirrors findings from previous ISM-based research, where lower-level constructs acted as driving forces shaping higher-order outcomes [19, 22]. The present model, therefore, confirms that developing individual autonomy and self-regulation creates the necessary preconditions for systemic learning and competitive advantage. At higher levels, components such as "enhanced self-confidence," "improved self-directed learning," and "performance improvement and competitive advantage" represent the long-term organizational impacts of sustained SDL practices. These results align with the theoretical perspective of Lounsbury et al. (2024), who posited that SDL should be conceptualized as a personality-based competence that directly predicts adaptability, resilience, and innovation capacity in professional contexts.

The results also demonstrate that "creative inquiry," "semantic expansion," and "repetition and review strategies" constitute essential cognitive mechanisms supporting SDL in organizational learning. These strategies were identified as operational indicators in the model, reflecting the role of metacognitive processes in learning efficiency [24, 26]. Previous research by Fisher et al. (2019) highlighted the necessity of metacognitive strategies for improving self-directed readiness, particularly in professional education settings. Similarly, Bembenutty (2019) found that learners who effectively manage cognitive strategies such as rehearsal and elaboration exhibit higher persistence and academic delay of gratification. In the current study, these strategies serve as dynamic processes that connect the cognitive and behavioral dimensions of SDL, enabling employees to transform passive knowledge acquisition into active problem-solving and innovation.

A particularly relevant finding concerns the influence of psychological and emotional dimensions on SDL behavior. The model suggests that factors such as "increased self-confidence" and "learning motivation" are both outcomes and reinforcers of self-directed learning. This reciprocal relationship is consistent with recent empirical studies linking SDL with psychological capital and emotional resilience [7, 15, 16]. Yang (2024) demonstrated that psychological capital mediates the relationship between stress and SDL ability, implying that positive emotions and self-efficacy enhance learners' capacity for independent learning. Similarly, Talebzadeh Shushtari and Boyeri (2024) identified achievement motivation as a mediating factor linking emotional creativity and critical thinking to SDL. The present study reinforces these findings by illustrating that emotional resources and motivational climates in the workplace directly influence self-directed learning readiness.

Moreover, the study confirms that "environmental dynamism" and "organizational hierarchy" play dual roles as both enabling and moderating conditions. This finding echoes the results of Sindhu et al. (2016) and Jindal and Sangwan (2013), who demonstrated in their ISM-based studies that contextual variables, such as structural complexity and environmental uncertainty, can either facilitate or constrain strategic decision-making processes. In the same way, SDL in complex organizations like banks is shaped by structural relationships among technological, cultural, and human subsystems. This contextual dependency aligns with the constructivist view that learning is situated within social and environmental systems [5, 25]. It also supports the findings of Khezri (2023), who found that participatory and integrated teaching methods improved self-regulation and performance in educational contexts by fostering learner autonomy and engagement.

From a methodological perspective, the combination of grounded theory and interpretive structural modeling proved particularly effective in uncovering the causal, contextual, and strategic dimensions of SDL in an organizational setting. Grounded theory allowed for the identification of latent constructs through open and axial coding [17, 18], while ISM facilitated the hierarchical classification of these constructs based on expert consensus [19]. The two-phase design not only validated the conceptual relationships among SDL components but also provided a practical framework for managerial decision-making. The application of this hybrid methodology supports previous research that emphasizes the value of combining qualitative exploration with structured modeling to build empirically grounded theories in management and education [21, 22].

Furthermore, the model underscores that "reward and evaluation systems," while not directly initiating SDL, play a crucial role in sustaining it. Positive reinforcement, recognition, and feedback loops motivate employees to pursue autonomous learning goals, aligning with earlier findings by Grover and Miller (2018), who noted that organizational incentives enhance commitment to lifelong learning [12]. Similarly, Pittayarat Yamprayoon and Jermtaisong (2020) argued that continuous evaluation and group learning activities can enhance motivation and retention in language education. Translating this insight into organizational practice, it can be inferred that feedback-rich environments foster the internalization of self-directed learning values and behaviors.

The integrative framework produced by this study thus provides both theoretical and practical implications. Theoretically, it advances the understanding of SDL by bridging individual and organizational learning theories, confirming that SDL operates within a systemic model where personal agency interacts with environmental affordances. The findings echo Moghadam Zadeh et al. (2018) and Hasanvandi (2019), who viewed self-directed learning as an institutional capability that strengthens adaptability and innovation capacity. Practically, the validated model offers a diagnostic tool for educational and training managers to assess the maturity of SDL implementation within their organizations. In particular, Bank Sepah's model demonstrates how individual learning autonomy can be cultivated through structured managerial support, technological infrastructure, and organizational culture.

The model also aligns with the global shift toward self-managed learning systems in modern organizations, where adaptability, resilience, and digital literacy have become critical performance indicators [13, 14]. The inclusion of experiential and implicit learning components reinforces the argument that SDL thrives when employees are encouraged to engage in reflective practice and continuous experimentation [24, 25]. This echoes the constructivist position that meaningful learning occurs when individuals interact with real-world problems in socially supported environments [5]. The present study thus bridges traditional self-directed learning frameworks with contemporary organizational and technological dynamics, providing a model that integrates human, structural, and cultural dimensions.

In conclusion, the research provides empirical validation for a comprehensive model of SDL management that connects individual psychological readiness, organizational context, and systemic enablers. By prioritizing individual capabilities, fostering learning culture, and leveraging ICT infrastructure, organizations like Bank Sepah can cultivate adaptive learners capable of meeting the demands of dynamic financial environments.

Despite its robust design, the study has several limitations. First, its sample was restricted to a specific organizational context—Bank Sepah—which may limit the generalizability of findings to other sectors or international contexts. The hierarchical structure of the banking industry and its regulatory environment could influence the applicability of the model to more flexible or creative industries. Second, the reliance on expert judgment for ISM modeling introduces a degree of subjectivity, as the experts' perspectives may reflect organizational norms and biases rather than universally applicable principles. Third, although the mixed-method approach integrated qualitative and quantitative phases, the study primarily focused on structural relationships rather than longitudinal behavioral change, thus limiting insights into how SDL evolves over time within individuals and teams.

Future studies could expand the present model by testing it across diverse organizational settings, such as educational institutions, technology firms, and governmental agencies, to examine its external validity. Quantitative structural equation modeling (SEM) could also be employed to statistically confirm the causal relationships identified through ISM. Longitudinal designs would help explore the evolution of self-directed learning behaviors and their long-term effects on organizational performance. Moreover, future research could integrate cross-cultural comparisons to determine how sociocultural factors and leadership styles influence SDL adoption and sustainability. Investigating the role of artificial intelligence and adaptive learning technologies in enhancing self-directed learning readiness would also contribute to the modern understanding of digital learning ecosystems.

Practically, organizations should invest in strengthening individual learning capabilities through targeted training programs that promote autonomy, reflection, and problem-solving. Managers should establish a supportive learning culture by integrating SDL principles into performance appraisal and reward systems. Technological infrastructure must be optimized to facilitate access to learning resources, peer collaboration, and feedback mechanisms. Additionally, leadership teams should adopt participatory management styles that empower employees to take ownership of their professional development. Finally, embedding SDL frameworks within organizational training policies can enhance resilience, innovation, and sustainable growth in the face of changing market and technological conditions.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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