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Learning innovation management to elevate labor competitiveness within the Thai food industrial sector

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Abstract: This research examines learning innovation management as a systemic framework for enhancing labor competitiveness in the Thai food industry. Amid increasingly volatile competition driven by automation, digital supply chains, and sustainability standards, this study develops a conceptual model linking key determinants, including learning innovation management, organizational factors, human capital investment, and upskilling and reskilling initiatives. A quantitative research design was employed, and data were collected from 340 professionals working in the Thai food sector. Structural Equation Modeling (SEM) was utilized to test the hypothesized relationships among variables. The findings reveal that learning innovation management has a significant direct influence on both upskilling and reskilling development, as well as on organizational readiness. However, its direct impact on competitiveness enhancement was not statistically significant. Instead, learning innovation management contributes indirectly to competitiveness through mediating variables, particularly human capital development and organizational capability. The overall model explains 49.7% of the variance in competitiveness enhancement (R^2 = 0.497). These results provide important implications for policymakers and industry leaders in designing effective learning systems that bridge skill gaps, strengthen workforce adaptability, and enhance long-term industrial competitiveness in the digital economy.

Keywords: *Competitiveness enhancement, Human capital investment, Learning innovation, Management, Organizational factors, Thai Food Industry, Upskilling and reskilling.*

1. Introduction

1.1. Research background

The Thai food industry serves as a cornerstone of the national economy, significantly contributing to revenue generation and providing extensive employment opportunities. However, the sector is currently navigating a period of rapid and volatile competition, propelled by the integration of advanced technologies, automation, digital supply chains, and evolving standards for safety and sustainability. Consequently, enterprises are compelled to accelerate their adaptation strategies to maintain a competitive advantage [1]. Projections for 2025 indicate a sustained trend of investment, characterized by the expansion of production capacities and the introduction of innovative product lines, particularly within the ready-to-eat, processed food, and health-oriented segments. These developments are strategically aligned with infrastructure investments in industrial estates, processing facilities, and distribution hubs across high-potential regions, including Bangkok, Chonburi, Chiang Mai, and Surat Thani. Furthermore, the industry faces mounting pressure from foreign direct investment, notably from Chinese investors who are consistently increasing capital in food and beverage processing businesses for export purposes [2]. Broadly, the agricultural and food sectors remain the primary economic base of the country in terms of GDP, export value, and labor force participation. Despite this strength, the industry

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must contend with global headwinds, such as geopolitical tensions, climate volatility, stringent trade regulations, and the challenges of an aging society. To address these issues, it is imperative to "transform" the industry toward *Future Food* as a new economic engine. This transition prioritizes health, sustainability, and the application of technology and innovation, categorized into four primary groups: (i) Functional Foods and Ingredients: Focused on health-enhancing properties beyond basic nutrition. (ii) Medical and Personalized Food: Tailored to specific medical needs or individual health profiles. (iii) Organic and Minimally Processed Products: Emphasizing natural purity and sustainability. (iv) Alternative Proteins: Developed to meet the rising demand for plant-based and sustainable protein sources. These segments are poised for high growth in alignment with the increasing global demand for health-conscious and sustainable food products [3].

Despite its high potential, the food industry is currently confronted with rising operational costs and a critical shortage of specialized labor, particularly in the fields of food science, digital production technology, data analytics, and modern innovation management. Concurrently, a substantial portion of the workforce requires urgent reskilling and upskilling to integrate with emerging technologies, as some roles face the risk of displacement by automation, robotics, and Artificial Intelligence (AI). Furthermore, enterprises, especially Small and Medium Enterprises (SMEs), are hindered by high initial investment costs for innovation and a persistent 'skill gap' that prevents the full utilization of technological capabilities [4]. Consequently, achieving sustainable competitiveness necessitates a systemic approach that harmonizes labor skill development with robust innovation management.

A review of relevant literature indicates that upskilling and reskilling have gained significant prominence within the digital economy framework. Research by Arini and Respatiningsih [5] emphasizes that enhancing human resource capabilities in the digital era, particularly among Micro, Small, and Medium Enterprises (MSMEs), must encompass all labor skill levels [5]. This development requires a collaborative ecosystem involving the public sector, private enterprises, and relevant stakeholders to foster an environment conducive to competitive advantage. Furthermore, Rawashdeh investigates technological determinants influencing the adoption of Artificial Intelligence (AI) in organizations, highlighting the role of automation, such as automated accounting systems, as a mediating variable that improves decision-making efficiency and mitigates time constraints within SME workflows [6]. Collectively, these studies underscore the critical importance of digital technology and labor skills in bolstering overall organizational competitiveness.

Further analysis reveals a significant research gap; while existing studies predominantly focus on technological outcomes and automation factors, the dimension of *learning innovation management* remains underexplored. This management is a critical mechanism for preparing the workforce to utilize technology effectively, yet its application within the food industry, characterized by unique production processes, food safety standards, and diverse labor structures, is limited. Moreover, systematic research linking learning innovation management, skill development, and labor competitiveness in the Thai food industry is scarce. Consequently, there is a lack of mechanistic understanding regarding how to design and manage learning processes that truly respond to rapid technological shifts and industrial competition [7].

Under this conceptual framework, the study systematically explores learning innovation management as a vital mechanism for enhancing upskilling and labor competitiveness within the Thai food industry [8]. The research prioritizes characterizing the forms and intensities of learning innovation required to support effective reskilling and upskilling initiatives among the workforce. Furthermore, it analyzes critical determinants influencing labor competitiveness, encompassing job performance, adaptability, and innovative potential. A primary objective is to validate the consistency of the Structural Equation Model (SEM) against empirical data to confirm the model's fitness and elucidate the causal relationships between systemic variables, particularly the overarching influence of management factors [9, 10].

Further analysis reveals a significant research gap; while existing studies predominantly focus on technological outcomes and automation factors, the dimension of *learning innovation management* remains underexplored. This management serves as a critical mechanism for preparing the workforce to utilize technology effectively, yet its application within the food industry, characterized by unique production processes, food safety standards, and diverse labor structures, is notably limited. Moreover, systematic research linking learning innovation management, skill development, and labor competitiveness, specifically within the Thai food sector, remains scarce. Consequently, there is a clear lack of mechanistic understanding regarding the optimal design and administration of learning processes that can truly respond to rapid technological shifts and intense industrial competition.

1.2. Research Overview and Research Gaps

1.2.1. Human Capital Investment

Human capital investment is a fundamental strategic concept describing the deliberate allocation of organizational resources to enhance the knowledge, skills, and behavioral attributes of personnel [11]. These elements are increasingly recognized as an organization's most valuable intangible assets, serving as key drivers of productivity, organizational efficiency, and sustainable competitiveness [12]. Beyond formal schooling and technical expertise, human capital encompasses practical work experience, socio-emotional competencies, motivation, and creativity. These components form the foundation for establishing a sustainable competitive advantage at both micro-enterprise and macroeconomic levels. Scholarly consensus emphasizes that effective human capital investment comprises three core pillars: education and training, professional experience, and behavioral skills. Continuous education and training facilitate the acquisition of essential skills for technological integration, while professional experience enhances problem-solving capabilities in complex, real-world scenarios. Furthermore, behavioral attributes such as communication, leadership, and adaptability are critical for fostering a collaborative environment that ensures long-term organizational success [13]. Recent global trends also highlight personal qualities, including discipline and innovative thinking, as indispensable factors for navigating the shifts toward an AI-driven human workforce [14].

From a management perspective, organizations play a pivotal role in human capital development across the entire employment lifecycle, from strategic recruitment and job design to performance management and continuous learning. Such investments not only elevate overall business performance but also act as primary attractors and retainers for talent. However, human capital can depreciate if employees lack development opportunities or fail to adapt to emerging technologies. Consequently, a systemic approach that integrates lifelong learning systems with an environment conducive to sustainable growth is essential for maintaining a competitive edge in the evolving digital economy [15].

Literature reviews indicate a significant positive correlation between human capital investment and competitiveness. Shao et al. demonstrate that human capital, particularly when firm-specific, significantly enhances corporate performance and sustainable advantage [16]. Furthermore, Konings and Vanormelingen highlight that improving human capital structures, specifically increasing the proportion of highly educated and skilled employees, leads to higher quantity and quality of innovative outputs, such as patents, which drive technological and market competitiveness [17]. Based on these insights, this study hypothesizes that human capital investment exerts a direct positive influence on competitiveness enhancement.

Synthesizing these concepts, human capital investment is defined as a strategic process leveraging resources to develop employee knowledge, skills, experience, and potential to create value and sustainable productivity. Critical empirical factors of this investment include education and training, professional experience, and behavioral/social skills, all of which serve as observable variables for empirical analysis and model development in this research. Recent studies using Structural Equation Modeling (SEM) further confirm that strategic management of these human assets is the primary driver of organizational innovation and efficiency [13].

1.2.2. Learning Innovation Management

Learning innovation management represents a systematic administrative process encompassing the planning, design, implementation, and evaluation of educational innovations [18]. This approach aims to enhance learning quality and efficiency in response to rapid technological and societal shifts [10, 19]. The core of this management is to generate "outcome-based value," ensuring that learners gain practical benefits rather than just experiencing changes in instructional formats [20]. Effective learning innovation facilitates lifelong learning, creative collaboration, and empowered citizenship by utilizing flexible curricula and real-world project-based activities.

In an organizational context, learning innovation management is most effective when integrated into a *Learning Organization* culture. This ecosystem requires agile structures, knowledge transfer mechanisms, and the strategic use of supporting technologies such as AI tutors, AR/VR, and Digital Learning Platforms (LXP) to bridge digital skill gaps [9]. Empirical evidence indicates that innovation management is a decisive factor in competitive strategy, directly influencing organizational performance and efficiency. Practically, learning innovation management consists of three empirical dimensions:

- Competency-based instructional design: ensuring learning outcomes are applicable to real-world professional tasks.
- Digital Learning Experience Platforms (LXP): Providing flexibility and accessibility for training anytime and anywhere.
- Learning Analytics Dashboards: Utilizing empirical data to monitor, evaluate, and refine learning processes.

Furthermore, leadership styles and human capital play pivotal roles in driving these innovations toward organizational success. Well-designed learning systems enable the workforce not only to acquire knowledge but also to engage in critical analysis and creative application, ensuring sustainable growth in a competitive global market [7].

1.2.3. Upskilling and Reskilling

Upskilling and reskilling have emerged as the most critical strategic imperatives for labor adaptation within the global industrial landscape. Upskilling focuses on enhancing an employee's existing competencies to meet elevated performance standards in current roles, while reskilling involves training for fundamentally different positions necessitated by organizational restructuring [5]. These processes serve as the primary defense mechanisms against the widening skill gaps triggered by the integration of Industry 5.0 and AI-driven systems [19, 21].

From an economic perspective, consistent investment in these areas is inextricably linked to substantial gains in labor productivity and organizational value-added [22]. The effective implementation of these strategies, particularly in the food industry, involves several key dimensions:

- Systemic Productivity: Enhancing human capital structures by increasing the density of high-skilled labor through targeted reskilling leads to a measurable improvement in innovation quality and patentable outputs [17].
- Technological Fluency: In the modern manufacturing context, upskilling is no longer limited to basic technical tasks but extends to advanced data literacy and the collaborative management of automated processes [23].
- Strategic Resilience: Organizations that embed a "lifelong learning culture" into their operational framework exhibit higher levels of resilience and are better positioned to maintain a global competitive edge during market volatility [24].

Ultimately, upskilling and reskilling are not isolated training events but are foundational elements of a systemic human resource development strategy. By aligning individual skill trajectories with long-term organizational goals, enterprises in the Thai food sector can ensure sustainable growth and global competitiveness.

1.2.4. Organizational Factors

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Organizational factors represent the internal conditions and structural attributes that determine an enterprise's capacity to manage resources and sustain competitiveness [18]. These factors act as the "foundational engine" that translates strategic vision into operational excellence, particularly in volatile market environments [25]. In the context of the Thai food industry, several critical dimensions of organizational factors influence the success of learning innovation:

- Strategic Leadership and Vision: Leadership is the primary catalyst for fostering an innovative culture and motivating personnel to embrace change. Modern research indicates that "Ambidextrous Leadership," the ability to balance current operational efficiency with future innovation, is vital for navigating the digital transition in manufacturing [26].
- Organizational Resources and Technological Readiness: The effective mobilization of knowledge, financial capital, and technological infrastructure is essential for creating product differentiation. Current evidence suggests that an organization's "Digital Maturity" is a stronger predictor of competitiveness than mere resource availability [27].
- Structural Agility and Organizational Size: While larger organizations possess greater capacity for large-scale training investments, smaller, more agile structures often demonstrate higher speeds of innovation adoption. In the post-2025 landscape, "Structural Fluidity," the ability to reconfigure teams and processes rapidly, has become a decisive factor in maintaining a global competitive edge [28].

In summary, organizational factors do not merely provide a background for learning innovation but are active determinants of its intensity and success. By aligning internal structures with external technological shifts, enterprises can effectively leverage human capital to achieve sustainable growth [25].

1.2.5. Competitiveness Enhancement

The concept of "competitiveness" gained significant prominence in the 1980s, initially as a strategic response to global market shifts. In the modern era of rapid technological transition and borderless trade, competitiveness has evolved beyond mere "low-cost" advantages. It now encompasses the ability to produce goods and services efficiently while continuously elevating quality, value, reliability, and innovation to create sustainable differentiation. For Thailand, especially following the 1997 economic crisis, the national strategy has focused on restructuring competitiveness across three levels: the macro level (infrastructure and global role), the sectoral level (innovation and workforce excellence), and the social level (enabling environments for quality of life) [7].

Theoretically, Michael Porter posits that national wealth and quality of life depend on the productivity of human, capital, and natural resources. This is reflected in the *Diamond Model*, which identifies four interrelated determinants: (i) Factor Conditions (knowledge and infrastructure), (ii) Demand Conditions (sophisticated domestic needs), (iii) Related and Supporting Industries (cluster-based innovation), and (iv) Firm Strategy, Structure, and Rivalry. In the current global landscape, this micro-level advantage is increasingly driven by "Dynamic Capabilities," the ability to integrate and reconfigure internal competencies to address rapidly changing environments [29].

Within contemporary research frameworks, competitiveness enhancement is empirically measured through four key dimensions: maintaining continuous advantage, growth in market share and profitability, long-term market presence, and cultivating a workforce characterized by high motivation and lifelong learning. Critical catalysts for these dimensions include:

- Human Capital Transformation: Through systematic upskilling and reskilling initiatives.
- Digital Integration: Leveraging Industry 5.0 technologies to optimize production processes.
- Organizational Agility: Maintaining flexible structures and resource management strategies to respond to global volatility.
- Policy Support: Utilizing national infrastructure and government incentives to reduce costs and enhance industrial efficiency.

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In summary, enhancing competitiveness is a systemic endeavor where human capital and learning innovation serve as the core engines for sustainable global positioning [5, 30].

2. Research Objectives

The primary objectives of this study are categorized as follows:

Objective 1: To investigate the influence of learning innovation management on enhancing labor competitiveness within the Thai food industry. This objective focuses on how systematic learning frameworks drive competitive outcomes in a rapidly evolving technological landscape.

Objective 2: To develop and validate a Structural Equation Model (SEM) representing the causal relationships between learning innovation management and labor competitiveness enhancement in the Thai food industry. The model aims to provide rigorous, empirical confirmation of the conceptual framework through advanced statistical analysis.

3. Research Methodology

3.1. Sampling and Data Collection

This study employs a quantitative research design, specifically utilizing Structural Equation Modeling (SEM) to analyze complex causal relationships. To ensure statistical power and model fit, the sample size was determined based on the ratio of observations to the number of independent parameters (observed variables). Following the established criteria by Hair et al. [31], which suggest a minimum ratio of 20 samples per parameter, this research identified 17 key parameters [31, 32]. Consequently, a total sample size of 340 respondents was established, providing sufficient robustness for the SEM analysis [33].

The study utilized simple random sampling to select participants from a pre-defined sampling frame of individuals with homogeneous characteristics within the Thai food industry. The target population included executives, engineers, and department heads who possess direct insight into organizational learning and innovation management. Data collection was executed through a multi-channel approach, including:

- On-site surveys at industrial facilities.
- Online questionnaires distributed via professional networks.
- Electronic mail (E-mail) invitations.

Following the collection phase, all returned questionnaires underwent rigorous data cleaning and integrity checks to ensure completeness and validity before proceeding to the data analysis stage.

3.2. Data Analysis

The data analysis for this study was performed using SmartPLS software. The analytical procedure was divided into three primary stages to ensure the robustness and validity of the structural model:

3.2.1. Preliminary Analysis and Multicollinearity Check

Initially, Pearson's Product-Moment Correlation Coefficient was calculated to examine the preliminary relationships between variables. To mitigate the risk of multicollinearity, the correlation coefficients were assessed against the threshold of 0.70, ensuring that the variables do not exhibit excessive common variance that could distort the structural estimates [34].

3.2.2. Measurement Model Assessment

The measurement model was evaluated through the following rigorous criteria:

- Reliability and Convergent Validity: Assessed by examining factor loadings and average variance extracted (AVE), with both requiring values greater than 0.50 to demonstrate that the constructs explain more than half of the variance of their indicators [31, 35].
- Discriminant Validity: Evaluated using the Composite Reliability (CR) with a threshold of > 0.60 [36]. Furthermore, the Heterotrait-Monotrait Ratio (HTMT) was utilized as a more stringent

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criterion for establishing discriminant validity in higher-order constructs, ensuring each construct is empirically distinct [37].

3.2.3. Structural Model Assessment

The final stage involved evaluating the hypothesized paths within the structural model. The significance of paths was determined using the bootstrap resampling method, with the following criteria for hypothesis confirmation:

- p-value < 0.05 or t-statistics > 1.96.
- The alignment between empirical data and the theoretical framework was verified to confirm the validity of the structural equations and their predictive power [38].

This multi-stage analytical approach ensures that the findings are statistically sound and capable of providing meaningful insights into labor competitiveness within the Thai food industry [39].

4. Research Findings

4.1. Measurement Model Assessment

The measurement model was assessed prior to structural model testing to ensure that the core constructs were measured with adequate reliability and validity. Because learning innovation management, competitiveness enhancement, upskilling and reskilling, human capital investment, and organizational factors were specified as multidimensional constructs, the assessment considered both lower-order dimensions and higher-order constructs. The indicator loadings were consistently high, and the reliability and convergent validity statistics were all within acceptable thresholds. Overall, the reflective dimensions demonstrated satisfactory measurement quality, with strong factor loadings and acceptable discriminant validity. In particular, Cronbach's alpha, rho A, composite reliability, and AVE all supported adequate internal consistency and convergent validity.

At the higher-order level, learning innovation management, competitiveness enhancement, upskilling and reskilling, human capital investment, and organizational factors all exhibited AVE values ranging from .70 to .80, exceeding the recommended threshold of .50 and indicating strong reliability and acceptable convergent validity. Composite reliability values were also high, ranging from .80 to .90, suggesting strong construct stability. Additionally, all indicators loaded significantly on their intended constructs, with loadings above .50 and p-values below .05. These results confirm that the indicators were significantly associated with their respective factors and that the measurement model was statistically appropriate. Specifically, the dimensions of organizational factors loaded positively and significantly on the higher-order construct (β = .810-.882, $p < .001$). Human capital investment also showed strong and significant loadings (β = .838-.880, $p < .001$), as did learning innovation management (β = .816-.875, $p < .001$), upskilling and reskilling (β = .830-.877, $p < .001$), and competitiveness enhancement (β = .812-.862, $p < .001$). Table 1 reports the reliability and convergent validity of the higher-order constructs and their dimensions.

Table 1.
Reliability and Convergent Validity of the Higher-Order Constructs.

Higher-order construct	Dimension	β	SE	t-value	p-value	Cronbach's α	rho_A	CR	AVE
Learning Innovation Management	LCP	0.875	0.051	16.548	< 0.001	0.792	0.804	0.878	0.706
	LLA	0.816	0.062	10.992	< 0.001				
	LLM	0.828	0.062	11.621	< 0.001				
Organizational Factors	LEAD	0.882	0.042	19.648	< 0.001	0.804	0.812	0.884	0.718
	RESO	0.849	0.043	17.780	< 0.001				
	SIZE	0.810	0.050	13.874	< 0.001				
Up-skilling	CHANGE	0.830	0.042	18.422	< 0.001	0.872	0.875	0.913	0.723
	HC	0.859	0.038	20.389	< 0.001				
	MOTI	0.877	0.033	26.240	< 0.001				
	NEED	0.833	0.045	16.949	< 0.001				
Human Capital	EDU	0.838	0.044	15.754	< 0.001	0.832	0.840	0.899	0.748

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Investments	SS	0.880	0.035	23.556	< 0.001				
	WE	0.876	0.039	21.580	< 0.001				
Competitiveness.	GROWTH	0.850	0.031	26.292	< 0.001	0.866	0.871	0.908	0.712
	LIFE	0.851	0.032	25.396	< 0.001				
	LONG	0.812	0.041	16.459	< 0.001				
	SCA	0.862	0.032	26.105	< 0.001				

Note: CR = composite reliability; AVE = average variance extracted.

Table 2 reports the HTMT values for the higher-order constructs, supporting discriminant validity. All HTMT values among the five focal constructs were below the conservative threshold of 0.85: Human-Advantage (0.665), Learning-Advantage (0.521), Learning–Human (0.723), Organization-Advantage (0.634), Organization-Human (0.552), Organization–Learning (0.377), Upskill-Advantage (0.722), Upskill–Human (0.665), Upskill–Learning (0.454), and Upskill Organization (0.709). Discriminant validity among the main constructs was confirmed.

Table 2.
Discriminant Validity of the Higher-Order Constructs (HTMT).

Construct	Advantage	Human	Learning	Organization	Upskill
Advantage	—				
Human	0.665	—			
Learning	0.521	0.723	—		
Organization	0.634	0.552	0.377	—	
Upskill	0.722	0.665	0.454	0.709	—

Note: HTMT = heterotrait–monotrait ratio. All HTMT values were below the conservative threshold of .85, supporting discriminant validity among the focal higher-order constructs.

4.2. Structural Model Analysis

After establishing the adequacy of the measurement model, the structural model was evaluated to test the proposed hypotheses. Collinearity diagnostics indicated that no serious multicollinearity problems were present among the predictor constructs. In this study, path significance was assessed using t-values and p-values, with t-values greater than 1.96 and p-values below 0.05 indicating statistical significance.

The structural model results showed that learning innovation management had a positive and significant effect on upskilling and reskilling (β = 0.454, t = 8.217, p < 0.001) and a positive and significant direct effect on organizational factors (β = 0.375, t = 6.233, p < 0.001). However, learning innovation management did not have a statistically significant direct effect on competitiveness enhancement (β = 0.127, t = 1.477, p = 0.140). This relationship should therefore be interpreted as statistically weak rather than empirically supported.

In addition, organizational factors were positively associated with human capital investment (β = 0.555, t = 10.955, p < 0.001) and competitiveness enhancement (β = 0.204, t = 2.689, p = 0.007). Human capital investment also had a positive effect on competitiveness enhancement (β = 0.201, t = 1.960, p = 0.050). Similarly, upskilling and reskilling were positively associated with competitiveness enhancement (β = 0.387, t = 4.505, p < 0.001). Table 3 presents the direct structural relationships and the results of the corresponding hypothesis tests.

Table 3.
Direct Effects and Hypothesis Testing.

Hypothesis	Path	β	SE	t-value	p-value	f^2	Decision
H1	Learning -> advantage	0.127	0.086	1.477	0.140	0.020	Not Supported
H2	Learning -> Upskill	0.454	0.055	8.217	< 0.001	0.169	Supported
H3	Learning -> Organization	0.375	0.060	6.233	< 0.001	0.101	Supported
H4	Organization -> advantage	0.204	0.076	2.689	0.007	0.047	Supported
H5	Organization -> Human	0.555	0.051	10.955	< 0.001	0.266	Supported

H6	Human -> advantage	0.201	0.103	1.960	0.05	0.041	Supported
H7	Upskill -> advantage	0.387	0.086	4.505	< 0.001	0.130	Supported

As shown in Table 3, hypotheses H2, H3, H4, H5, H6, and H7 were supported, whereas hypothesis H1 was not supported.

4.3. Indirect Effects and Mediation Analysis

The indirect effects analysis was conducted to examine the mediating roles of the proposed variables in the relationships between the independent and dependent constructs. The results showed that the indirect effect of learning innovation management on competitiveness enhancement through upskilling and reskilling was positive and statistically significant ($\beta = 0.176$, $t = 3.932$, $p < 0.001$). The indirect effect of learning innovation management on competitiveness enhancement through organizational factors was also positive and statistically significant ($\beta = 0.077$, $t = 2.481$, $p = 0.013$). In addition, learning innovation management had a positive and statistically significant indirect effect on human capital investment through organizational factors ($\beta = 0.208$, $t = 4.538$, $p < 0.001$).

However, two indirect relationships were not statistically significant. The indirect effect of organizational factors on competitiveness enhancement through human capital investment was not significant ($\beta = 0.112$, $t = 1.930$, $p = 0.054$). Likewise, the indirect effect of learning innovation management on competitiveness enhancement through organizational factors and human capital investment was not statistically significant ($\beta = 0.042$, $t = 1.744$, $p = 0.081$). Table 4 presents the indirect effects and mediation results for the proposed model.

Table 4.
Indirect Effects and Mediation Results.

Hypothesis	Indirect path	β	SE	t-value	p-value	Decision
H8	Organization -> Human -> Advantage	0.112	0.058	1.930	0.054	Not Supported
H9	Learning -> Upskill -> Advantage	0.176	0.045	3.932	< 0.001	Supported
H10	Learning -> Organization -> Advantage	0.077	0.031	2.481	0.013	Supported
H11	Learning -> Organization -> Human -> Advantage	0.042	0.024	1.744	0.081	Not Supported
H12	Learning -> Organization -> Human	0.208	0.046	4.538	< 0.001	Supported

As shown in Table 4, hypotheses H9, H10, and H12 received empirical support, whereas hypotheses H8 and H11 did not receive empirical support.

These findings are theoretically meaningful. Although the direct effect of learning innovation management on competitiveness enhancement was not statistically strong, the indirect pathway through upskilling and reskilling was more substantial. This indicates that upskilling and reskilling may operate as important mechanisms through which learning innovation management contributes to competitiveness enhancement. In other words, the role of learning innovation management appears to be more influential when its impact is transmitted through workforce skill development than when it is considered an isolated direct predictor. Given the coexistence of both direct and indirect effects in the model, the mediation pattern is more appropriately interpreted as partial rather than full mediation.

The model showed a moderate level of explanatory capability. Learning innovation management accounted for 14.5% of the variance in upskilling and reskilling ($R^2 = 0.145$) and 9.2% of the variance in organizational factors ($R^2 = 0.092$). Organizational factors explained 21.0% of the variance in human capital investment ($R^2 = 0.210$). When learning innovation management, organizational factors, human capital investment, and upskilling and reskilling were incorporated together, the model explained 49.7% of the variance in competitiveness enhancement ($R^2 = 0.497$).

The effect size results also help clarify the relative contribution of each construct. Learning innovation management had a moderate effect on upskilling and reskilling ($f^2 = 0.169$), a small-to-moderate effect on organizational factors ($f^2 = 0.101$), and a small direct effect on competitiveness enhancement ($f^2 = 0.020$). Moreover, organizational factors ($f^2 = 0.047$), human capital investment ($f^2 = 0.041$), and upskilling and reskilling ($f^2 = 0.130$) each contributed additional explanatory value to competitiveness enhancement. Table 5 presents the explanatory power of the model along with the descriptive model fit index, while Figure 1 illustrates the final model.

Table 5.
Explanatory Power and Model Fit.

Endogenous construct / Index	Value	Interpretation
Competitiveness enhancement (Advantage)		
R^2	0.497	Moderate explanatory power
Adjusted R^2	0.491	Suggests the model explains a meaningful proportion of the competitiveness variance
Human capital investment (Human)		
R^2	0.210	Moderate explanatory power
Adjusted R^2	0.208	Indicates meaningful variance explained by Organizational factors
Organizational factors (organization)		
R^2	0.092	Weak to moderate explanatory power
Adjusted R^2	0.089	Indicates meaningful variance explained by learning innovation Management
upskilling and reskilling (upskill)		
R^2	0.145	Weak to moderate explanatory power
Adjusted R^2	0.142	Indicates meaningful variance explained by learning innovation Management
Model fit		
SRMR	0.054	Descriptively acceptable model fit

Note: R^2 values indicate the proportion of variance explained in each endogenous construct. Adjusted R^2 values account for model complexity. SRMR = standardized root mean square residual. In line with current PLS-SEM guidance, SRMR is reported as a descriptive fit index, whereas model evaluation relies more substantively on measurement quality, path coefficients, indirect effects, and explanatory power.

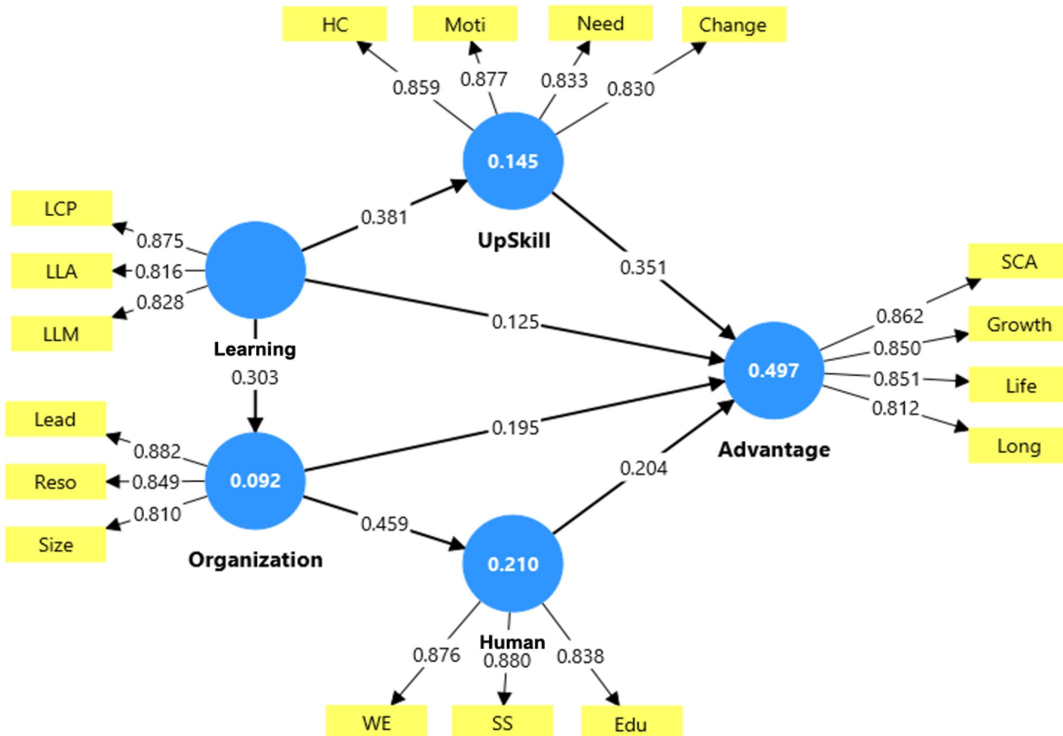

Figure 1.
Final Structural Model of the Study.

5. Discussion

Thailand's food industry remains a vital pillar of the national economy in terms of value creation, exports, and employment. Recent policy and industry reports continue to position the broader agri-food sector as a major economic base, contributing substantially to GDP, exports, and workforce participation, while Thailand's processed food exports reached approximately US$28 billion in 2024 [40]. At the same time, the sector is operating under intensifying competitive pressure driven by technological change, automation, digitalization, and increasingly demanding food safety and sustainability requirements. Thai industrial surveys further suggest that digital adoption is expanding, but many manufacturers are still at relatively early stages of transformation and continue to face constraints related to digital capability, skills, and funding [41]. In parallel, Thailand has elevated "future food" as a strategic growth area, with policy support directed toward health food, novel food, organic food, and related high-value segments. Taken together, these developments indicate that sustainable competitiveness in Thailand's food industry depends not only on technological upgrading but also on the systematic development of workforce capabilities and learning systems that can translate technological investment into productivity and market performance [42].

A review of recent literature shows that many studies have focused primarily on the outcomes of technology adoption, digital transformation, leadership, human capital, or organizational competitiveness. Current evidence also suggests that skills gaps remain one of the most important barriers to organizational transformation, particularly in environments shaped by AI, automation, and rapid shifts in business models. In the Thai context, recent analysis has also highlighted emerging talent shortages in food-science-related occupations and the structural limitations of small firms in attracting or retaining highly skilled personnel. However, comparatively less attention has been given to learning innovation management as a systemic mechanism that enables workers to use technology effectively and allows organizations to convert technological and human capital investments into competitiveness outcomes. Against this background, the present study addresses an important gap by positioning learning innovation management as an upstream driver of competitiveness that operates both directly and indirectly through workforce upskilling and reskilling, as well as through enhanced organizational readiness.

The study makes three principal contributions. First, it highlights the role of learning innovation management as a systemic mechanism linking technological transition with workforce development and competitive performance. Second, it integrates individual-level constructs, such as human capital investment and workforce skills, with organizational-level constructs, including leadership, resources, and organizational conditions, thereby offering a more comprehensive explanation of competitiveness enhancement. Third, it demonstrates the value of structural equation modeling for empirically testing the interrelationships among these constructs in a coherent analytical framework. The findings suggest that the contribution of learning innovation management to competitiveness is not merely a matter of direct influence; rather, its effect becomes more meaningful when it strengthens workforce upskilling and reskilling and reinforces organizational conditions that support capability development. This interpretation is consistent with recent scholarship emphasizing the strategic importance of learning-oriented leadership, human capital, and organizational learning in sustaining innovation and competitiveness.

At the same time, several limitations should be acknowledged. The strength of the observed relationships may vary across different food-manufacturing contexts, such as product category, regulatory intensity, production complexity, and degree of automation [43]. Heterogeneity may also emerge across firm size, particularly in an industry structure where smaller enterprises may face tighter constraints in technology adoption, talent acquisition, and long-term capability investment. In addition, abstract constructs such as learning culture, leadership quality, and organizational readiness require careful operationalization to reduce the risk of self-report bias. Future studies should therefore refine measurement instruments, test the model across more diverse subsectors of Thailand's food industry, and compare SMEs with larger firms to improve the robustness and practical relevance of the findings. Ultimately, the long-term value of this research lies in its ability to inform the design of learning systems, training strategies, and workforce development policies aligned with Thailand's transition toward a more digital, innovation-driven, and globally competitive food industry.

6. Policy Recommendations

Based on the present findings, policy support for Thailand's food industry should move beyond one-off training activities and instead promote a sector-wide learning system that links technological change with workforce capability development. Because learning innovation management appears to enhance competitiveness primarily through upskilling and reskilling, as well as through stronger organizational conditions, national and industry-level interventions should prioritize competency-based learning pathways in digital production, automation, food safety, quality systems, data analytics, traceability, and AI-assisted operations. These pathways should be modular, stackable, and tailored to different occupational levels, including shop-floor workers, technicians, supervisors, and plant managers.

6.1. First, Systemic Workforce Upgrading and Reskilling

The government, through the Ministry of Industry and the Ministry of Higher Education, Science, Research and Innovation (MHESI), should establish a dedicated "Food Industry Skill Fund." This fund should incentivize SMEs to engage in upskilling and reskilling, particularly in areas like AI-driven quality control and sustainable processing. Policy should focus on bridging the gap for the 47,000 workers needed in the future food sector by 2029 [44].

6.2. Second, Accelerating Learning Innovation Platforms

The Digital Economy Promotion Agency (depa) and the National Food Institute (NFI) should co-develop Learning Experience Platforms (LXP) tailored for food manufacturing. These platforms should integrate AR/VR for technical training and local wisdom-informed food technology, enabling workers to access high-quality training regardless of firm size [41].

6.3. Third, Strengthening "Future Food" Ecosystems

To maintain a global competitive edge, the Board of Investment (BOI) should expand tax incentives for firms investing in "Future Food" segments, such as plant-based proteins and medical foods. This includes supporting R&D to move beyond contract manufacturing (OEM) toward brand ownership, which requires high-level food science competencies [45].

7. Conclusion

This research provides a comprehensive empirical analysis of the drivers behind labor competitiveness in Thailand's food industry. The findings confirm that Learning Innovation Management serves as a vital upstream mechanism that significantly influences competitive outcomes through both direct and indirect pathways. Specifically, it acts as a catalyst for workforce upskilling and reskilling, while simultaneously reinforcing organizational readiness in terms of leadership and resource allocation.

The study concludes that in the era of Industry 5.0, technological upgrading alone is insufficient to sustain a market edge. Instead, sustainable competitiveness is rooted in a "systemic alignment" where human capital investment is continuously translated into productivity through innovative learning systems. For the Thai food sector, which faces intensifying global pressure and evolving sustainability standards, the transition from traditional manufacturing (OEM) to innovation-driven brand ownership depends on the workforce's ability to master complex digital and food-science competencies.

Ultimately, this research fills a critical gap by demonstrating that learning innovation is not merely a supportive function but a strategic core that enables organizations to navigate technological disruptions and market volatility successfully. The long-term value of these insights lies in their ability to inform the design of integrated workforce development policies that align with Thailand's national vision of becoming a high-value, innovation-led "Kitchen of the World" in the global arena.

Institutional Review Board Statement:

Formal approval from an Institutional Review Board was not required under the research ethics policies of the College of Innovation and Industrial Management, King Mongkut's Institute of Technology Ladkrabang, Thailand, as the study involved non-sensitive survey procedures and posed minimal risk to participants. However, the research was conducted in strict accordance with the ethical principles of the Declaration of Helsinki. Informed consent was obtained from all participants prior to data collection. To ensure participant confidentiality, all data were strictly anonymized, and no personally identifiable information was collected or reported in the final analysis.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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