A Symbiotic Nexus of WBL and ACD: An AI-Informed Ex-Post Evaluation of PIAAC.

by

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AN ABSTRACT OF DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Adult Learning and Leadership
College of Education

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2026

Abstract

In today's rapidly evolving knowledge economy, adults must continually acquire, apply, and adapt knowledge across changing workplace and life contexts. Yet the literature continues to identify a persistent "knowing-doing" gap, in which learning opportunities at work do not consistently translate into improved cognitive performance or sustained workplace learning. To better understand this relationship, this study examined the bidirectional association between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) using an integrated framework combining a family of Structural Equation Modeling (SEM) with SEM-informed static policy optimization. Using data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC 2023), the study investigated whether workplace learning experiences, including learning at work, ICT use at work, reading use at work, writing at work, working to deadlines, and influence over work activities, are associated with adults' literacy, numeracy, and adaptive problem-solving skills, while simultaneously examining whether stronger cognitive skills are associated with greater engagement in workplace learning. Reflection through improving work organization or work processes was examined as a mediating mechanism, while demographic and employment characteristics were incorporated as exogenous covariates. Building on the SEM findings, SEM-informed static policy optimization compared observed workplace-learning actions across WBL-ACD states to identify actions associated with the highest expected cognitive outcomes. The findings provide partial support for reciprocal associations between workplace-based learning (WBL) and adult cognitive development (ACD). However, the evidence was asymmetric and model-dependent, with the ACD-to-WBL association demonstrating greater consistency across model specifications than the WBL-to-ACD association. Across cognitive domains, the policy optimization analyses further

demonstrated that the effectiveness of workplace-learning actions varied by WBL-ACD state, with digital learning emerging as the most advantageous strategy in high cognitive-development states, while training and collaborative learning were more beneficial in intermediate states. Overall, the study contributes an empirically grounded framework that integrates structural modeling with policy optimization to advance understanding of workplace learning and to inform evidence-based strategies for strengthening adult cognitive development.

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Table of Contents

List of Figures xiv
List of Tables xvi
Acknowledgements xvii
Dedication xviii
Preface xix
Chapter 1 - Introduction 1
Introduction 1
Background of study 2
Problem Statement 4
Purpose of Research 5
Conceptual Framework 6
Research Questions and Hypotheses 8
Research Design 8
Significance of Study 11
Theoretical Significance 11
Empirical Significance 12
Policy and Practice Significance 13
Societal Significance 13
Limitations/ Delimitations of the Study 13
Chapter Summary 15
Definition of Terms 16
Chapter 2 - Literature Review 19
Introduction 19
Work-Based Learning 20
Dimensions of WBL 21
Experiential or practical dimension 21
Reflective dimension 21
Collaborative or social dimension 21
Knowledge dimension 22

Skill development dimension 22
Contextual dimension 22
Lifelong orientation dimension 22
WBL's contribution to ACD 23
Mechanism Involved in the Contribution 23
Practice and Feedback 23
Reflection and Collaboration 24
Digital Tool Use and Task Complexity 24
Adult Cognitive Development (ACD): Literacy, Numeracy, APS 25
Core Dimensions of ACD 25
Literacy 25
Numeracy 25
Adaptive Problem-Solving (APS) 26
ACD's contribution to WBL 26
Mechanism Involved in the Contribution 27
Conceptual Framework 28
Symbiotic WBL-ACD Nexus Framework 28
Core Components and Assumptions 29
Affordances Layer of Work-Based Learning (WBL) 32
Mechanism Layer of how WBL becomes Cognitive Change 32
Reflective Practice 33
Metacognitive regulation 33
Self-Efficacy and Learning Agency 33
Skill Use and Deliberate Cognitive Practice 34
Outcomes Layer from Adult Cognitive Development 34
Conditional Layer for Structural conditioning and exogenous covariates shaping the WBL Affordances 34
Reciprocal Feedback Layer 35
Dynamics of Symbiotic Relationship 35
Enablers and Inhibitors of the Symbiosis 36
Feedback Processes in the WBL-ACD Symbiosis Nexus 37

Applications and Implications 38
Contextual Factors Shaping the WBL-ACD Symbiosis 39
Chapter Summary 39
Chapter 3 - Methodology 41
Introduction 41
Research Questions and Hypotheses 42
Research Design 42
Conceptual Alignment 46
Methodological Positioning and Original Contribution 49
Data Collection and Variables 50
Dataset Collection 50
Variables and Measures 53
Endogenous Variable Work-Based Learning (WBL) 54
Endogenous Variable Adult Cognitive Development (ACD) 56
Mediating Variable 58
Exogenous Control Variables 58
Workplace Learning Experiences: The Occupational Context 59
WBL-ACD State Representation 60
Instrumentation and Construct Validation 65
WBL and Mediator Indices 65
Reliability Tests and Construct Validity 66
Standardization and Scaling of ACD Measures 66
Missing Data Handling 67
Data Analysis Procedures 67
Data Cleaning and Organization 67
Data Analysis 68
Statistical-Based Data Analysis 69
Descriptive Statistics 69
Structural Equation Modeling (SEM) 69
Artificial-Intelligence (AI) Based Data Analysis 72

SEM – Informed Static Policy Optimization as an AI-Informed Ex-Post Evaluation Framework ... 72
Integration of SEM and Static Policy Optimization ... 76
Modeling Strategy ... 77
Diagnostics & Reporting ... 81
SEM Diagnostics and Thresholds ... 81
SEM-Informed Static Policy Optimization Diagnostics and Thresholds ... 82
Integrated Diagnostics and Thresholds SEM-Informed Static Policy Optimization ... 83
Ethical Considerations ... 83
Limitations of the Methods ... 84
Chapter Summary ... 86
Chapter 4 - Results ... 88
Introduction ... 88
Analytic Sample Description and Data Quality ... 88
Missing Data and Multiple Imputation ... 90
Evaluation of the Imputation Procedure ... 92
Distribution Preservation ... 92
Imputed Value Realism ... 93
Standardized Overlay ... 95
Correlation Structure Preservation ... 97
Sample Characteristics ... 98
Weighted Descriptive Statistics and Correlations ... 98
Comparison with full PIAAC sample to assess representativeness ... 99
Reliability of Workplace Learning ... 101
Internal consistency ... 101
Inter-item correlations and item retention decisions ... 102
Construct Validity ... 103
Confirmatory factor analysis results ... 103
Standardized loadings and construct validity ... 104
Composite Reliability and AVE ... 105
Summary of Data Characteristics ... 106

Structural Model: Reciprocal WBL-ACD Relationships (RQ 1) 106
Model comparison across literacy, numeracy, and APS 106
Reciprocal path estimates and directionality patterns 110
Diagnostics and numerical stability 115
Synthesis: Nature of the WBL-ACD Association 117
Mediation Analysis 120
Robustness Analyses 121
Structural Model-Informed Static Policy Optimization Findings (RQ 2) 124
SEM-informed Static Policy Optimization Framework 124
Comparative Action Effects 125
Optimal policy selection 125
Policy differentiation across WBL-ACD states 127
Bootstrap policy stability 129
Integrated answer to the research questions 132
Chapter 5 - Discussion 134
Introduction 134
Generalizability of the Findings and Implications for Static Policy Optimization 134
Discussion of Data Characteristics and Quality 135
Discussion of Research Question 1 136
The reciprocal association between WBL and ACD 136
WBL and ACD are statistically interconnected 136
Interpreting the Reciprocal Association: Evidence of Statistical Interdependence Rather Than Definitive Reciprocal Association 138
Role of workplace participation 141
Robustness of the WBL–ACD Relationship Across Alternative Model Specifications 144
Summary RQ 1 146
Discussion of Research Question 2 147
Implications of SEM-informed static policy optimization 147
No universal learning strategy 147
Digital Learning Emerges as the Preferred Strategy for High WBL–High ACD States 149

Training and Collaborative Learning Remain Important for Intermediate WBL–ACD States 149
Policy Stability of Optimized Workplace-Learning Recommendations 150
Summary RQ 2 152
Interpreting the Findings through the WBL-ACD Framework 152
Affordances Layer of Work-Based Learning (WBL) 153
Mechanism Layer: How WBL Becomes Cognitive Change 154
Outcomes Layer of Adult Cognitive Development (ACD) 155
The Conditional Layer 156
Structural Conditioning of WBL Affordances (Control) 156
Covariates (Exogenous Controls) 157
Bidirectional Association and SEM-Informed Static Policy Optimization 158
Bidirectional Association: WBL ↔ ACD 158
SEM-Informed Static Policy Optimization 159
Summary interpretation of the revised WBL-ACD Framework 160
Implications 161
Future Research 164
Concluding Discussion 165
References 167

List of Figures

Figure 2-1 Conceptual Framework describing the dynamic Model Assumptions for WBL-ACD Nexus. 30
Figure 3-1 The integrated quasi-experimental design captures the bidirectional WBL–ACD nexus via SEM and validates it through SEM-informed static policy optimization, illustrating a self-optimizing system where experience strengthens cognition and cognition enriches experience. 44
Figure 3-2 Alignment between Research Question and Research Design. 46
Figure 3-3 Timing and Schedule of Cycle 2 of the PIAAC survey 2023 in the US. 51
Figure 3-4 World Map showing participating countries in Cycle 2 of the PIAAC survey 2023. 53
Figure 3-5 Illustrates Labeled Pathways that Depict Direct, Indirect, Mediating, and Feedback Relationships 64
Figure 3-6 Summary of the SEM Equations 69
Figure 3-7 Statistical Path Diagram for the Simultaneous Equation Model of the Proposed Symbiotic WBL-ACD Nexus 72
Figure 3-8 SEM Informed Static Policy Optimization Framework 73
Figure 3-9 Modeling Strategy for SEM Informed Static Policy Optimization 78
Figure 4-1 Derivation of the Final Analytical Sample 89
Figure 4-2 Missing Data Profile and Imputation Methods for Study Variables. 90
Figure 4-3 Distribution Preservation Summary 92
Figure 4-4 Imputed Values Realism for Key Variables 93
Figure 4-5 Imputed Values Realism for Key Variables 94
Figure 4-6 Standardized Overlay across Key Variables 95
Figure 4-7 Correlation Structure Preservation (Δr) 97
Figure 4-8 Descriptive Statistics and Correlation Structure of the Main Study Variables 99
Figure 4-9 Comparison of the Analytical Sample with the Full U.S. PIAAC 2023 Sample 100
Figure 4-10 Summary of Reliability and Convergent Validity of WBL Measurements 101
Figure 4-11 Inter-item correlation for WBL- Full and WBL-Refined Composites 103
Figure 4-12 Summary of Fit Indices – Need to be developed for WBL-Full and WBL-Refined 103

Figure 4-13 Standardized CFA Loadings for Full and Refined WBL Measures 104
Figure 4-14 Comparative Model-fit profile across literacy, numeracy, and APS. 107
Figure 4-15 Standardized directional path coefficients from reciprocal SEM specifications across literacy, numeracy, and adaptive problem solving. 111
Figure 4-16 Comparison of standardized forward and reverse path coefficients across SEM specifications for literacy, numeracy, and adaptive problem solving. 118
Figure 4-17 Comparison of standardized forward and reverse path coefficients across SEM specifications for literacy, numeracy, and adaptive problem solving. 122
Figure 4-18 Comparative advantage of workplace-learning actions relative to no extra support across observed WBL–ACD states. 126
Figure 4-19 Difference between the optimal and second-best workplace-learning actions across observed WBL–ACD states. 128
Figure 4-20 Bootstrap stability of optimal workplace-learning policy selection across observed WBL–ACD state. 130
Figure 5-1 Revised WBL-ACD Framework with Findings 153

List of Tables

Table 1-1 Terms and Their Definitions 16
Table 2-1 Summarizes the Characteristics of Workplace Sectors, their Impact within the Symbiosis Framework, and Sector-Based Examples. 36
Table 3-1 The Integration of Adult Learning Theories with SEM -Informed Static Policy Optimization Analysis. 48
Table 3-2 Indicators used to operationalize the Work-Based Learning Construct. 55
Table 3-3 summarizes the ACD measures, PIAAC variable code, measurement level, and their respective brief description. 56
Table 3-4 Adult Cognitive Development Measures. 56
Table 3-5 Mediating Variable for the SEM Analysis. 58
Table 3-6 Exogenous Control Variables for the SEM-Informed Static Policy Optimization Analysis. 59
Table 3-7 Work-Based Learning experiences (policy optimization actions). 60
Table 3-8 WBL-ACD State Representation. 61
Table 3-9 Construction of the WBL–ACD State Space 62
Table 3-10 Competing Model Specifications Used to Evaluate the WBL-ACD Associations 79
Table 3-11 Diagnostics and Thresholds for Simultaneous Equation Modeling (SEM) 81
Table 3-12 Diagnostics and Thresholds for SEM-Informed Static Policy Optimization 82
Table 4-1 Sample Structure 98
Table 4-2 Reliability and Construct Validity of the Workplace Learning Measure 102
Table 4-3 Comparative performance of the best-fitting SEM specifications across cognitive domains 108
Table 4-4 Standardized reciprocal path estimates across literacy, numeracy, and adaptive problem solving 112
Table 4-5 Direct, indirect, and total effects of work-based learning on adult cognitive development (Model 1) 120
Table 4-6 Model 8 (2SLS) robustness estimates pooled across plausible values 123

Acknowledgements

I would like to express my sincere gratitude to my major advisor, Dr. Haijun Kang, for his guidance, encouragement, and support throughout my doctoral journey. His mentorship, thoughtful feedback, and commitment to academic excellence have been instrumental in shaping this dissertation and my development as a researcher. I am also grateful to my dissertation committee members, Drs. Susan Y. Biniecki, Farhan Saddique, and Weixing Song, for their valuable insights, constructive suggestions, and encouragement, which have strengthened the quality and direction of this research. Throughout this journey, I have been fortunate to receive guidance, encouragement, and support whenever I needed it. The generosity of mentors, colleagues, and others who willingly shared their knowledge and time has continually reminded me that academic and professional growth is never an individual endeavor.

I extend my appreciation to the faculty, colleagues, and mentors who have contributed to my academic and professional growth. My doctoral journey has provided invaluable opportunities to expand my knowledge, strengthen my research skills, and develop a deeper appreciation for interdisciplinary scholarship. I am especially thankful to Kansas State University for providing an academic environment that supported my intellectual curiosity and professional aspirations.

Finally, I express my deepest gratitude to my family for their unconditional love, patience, and unwavering belief in me. Their encouragement has been a constant source of strength throughout the challenges and milestones of this journey. I am especially grateful to my husband, Dr.Tirthankar Roy, for his understanding, sacrifices, and steadfast support. This accomplishment would not have been possible without the love and encouragement of those who stood beside me throughout this journey.

Dedication

I dedicate this dissertation to my father and my husband, whose unconditional love, unwavering support, and constant belief in me have been my greatest sources of strength and inspiration. To my family, for their encouragement and love throughout this journey. This achievement is not mine alone, but a reflection of the sacrifices, patience, and faith of those who have stood beside me every step of the way.

Preface

My journey as an evaluator has been shaped by the opportunity to work across diverse disciplines, including education, workforce development, public health, and community-based programs. These experiences have deepened my understanding of how evaluation can inform decision-making, improve programs, and address complex societal challenges. Over time, I developed a particular interest in quantitative evaluation methods and their potential to generate meaningful evidence from complex data. This interest gradually evolved into a broader curiosity about how advanced statistical modeling and artificial intelligence (AI) could strengthen evaluation practices and support evidence-informed decisions.

Working with large-scale datasets has further shaped my research interests, particularly in understanding patterns, relationships, and inequalities that influence learning and development across populations. My professional experiences have also strengthened my interest in workforce development across different sectors, where opportunities for learning, skill acquisition, and professional growth are closely connected to individual and organizational outcomes. These interests motivated me to explore the relationship between workplace-based learning and adult cognitive development, drawing on nationally representative assessment data and quantitative analytical approaches.

This dissertation represents the intersection of my professional experiences, methodological interests, and commitment to advancing evaluation research. By integrating structural equation modeling with an AI-inspired, assessment-informed static optimization framework, I sought to explore how large-scale assessment data could be translated into meaningful insights for workforce learning and development. Beyond its empirical findings, this research reflects my broader aspiration to bridge quantitative research, evaluation, and emerging

computational approaches to support more equitable and effective learning opportunities. I hope this work contributes to ongoing conversations about the role of evidence, innovation, and interdisciplinary thinking in advancing adult education and workforce developmen

Chapter 1 - Introduction

Introduction

In today's rapidly evolving workplace, adults must be able to apply their learning effectively to real-life decision-making, both for personal and professional development, as well as for the collective advancement of society. However, research consistently reveals a persistent "knowing–doing gap" at workplace, a disconnect between what adults learn at work and how they apply what they learn in everyday decision making (Brion & Cordeiro, 2017; Butler et al., 2012; Fauth & Gonzalez-Martinez, 2021; Hulme, 2014; Lave & Wenger, 1991; OECD, 2019; Reder & Klatzky, 1994; Wilson, 2007). This weak integration of workplace learning into real-life decision-making undermines the broader goals of lifelong learning and raises critical concerns about the effectiveness and relevance of workplace learning practices. This learning–application gap at the workplace is closely aligned with the United Nations' Sustainable Development Goal (SDG) 4, Quality Education, notably Target 4.4, which calls for a substantial increase by 2030 in the number of youth and adults with "relevant skills, including technical and vocational skills, for employment, decent work, and entrepreneurship"(Ventura et al., 2025, p. 3).

In the meantime, findings from the Program for the International Assessment of Adult Competencies (PIAAC) highlight one of the most pronounced manifestations of this gap: adaptive problem-solving (APS), a key dimension of Adult Cognitive Development (ACD). PIAAC results indicate that a large proportion of adults across OECD countries struggle to apply even basic literacy, numeracy, and digital skills to everyday decision-making. For instance, in the United States, only 34% of adults demonstrated proficiency at Levels 2 or 3 in the problem-

solving dimension, meaning they could handle multi-step, inferential, or non-routine digital tasks (OECD, 2016). Conversely, the majority faced difficulties with basic navigation, critical thinking, and the application of skills.

Bridging this gap is essential for enhancing the quality of adults' decision-making across various sectors, such as Healthcare, STEM/Technical, Management/Business, Culinary/Food, and Education. To address this challenge, this study proposes examining the dynamic and reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). It seeks to develop an empirically grounded, AI-informed framework that first tests the existence of a reinforcing nexus between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) empirically. The framework then examines how workplace experiences are associated with cognitive development, adaptability, and lifelong learning capacity, while allowing the strength and direction of these relationships to be determined empirically.

Background of study

The background of this study arises from a persistent problem in adult learning, the failure to transfer learned skills from the workplace to daily life contexts. Research indicates that while adults acquire substantial knowledge and skills at work, only about 10–40% of this learning is translated into long-term or practical applications (Blume et al., 2010). As a result, learning retention decays over time, and the benefits of training diminish rapidly. This "disconnect" between learning and application has far-reaching consequences, including cognitive stagnation (Sitzmann & Weinhardt, 2018), weakened personal decision-making (Reyna & Farley, 2006), and reduced resilience (Fletcher & Sarkar, 2013).

Work-based learning (WBL), the process of acquiring skills, solving problems, and engaging in professional development through work, is a primary mode of adult learning and

cognitive development as adults spend a significant portion of their lives in workplaces (Illeris, 2002; Noe & Ellingson, 2017). When WBL is not effectively integrated into real-life decision-making, adults risk underutilizing acquired skills, making poorer decisions, and losing motivation for lifelong learning, all of which can lead to skill decay (Bronfman, 2007). Recent estimates suggest that only about 12% of learners consistently apply new skills beyond their immediate job context (Ford, 2024).

Although quantitative data on the extent of cognitive improvement resulting from applying workplace learning to real-life decision-making are limited, research on training transfer demonstrates that the application of learned competencies is shaped by learner characteristics, training design, opportunities to apply learning, and supportive work environments (Blume et al., 2010; Grossman & Salas, 2011). Understanding how WBL contributes to Adult Cognitive Development (ACD), including literacy, numeracy, and adaptive problem-solving, can therefore illuminate pathways to strengthen knowledge transfer from workplace to life-wide contexts.

Findings from the OECD's Program for the International Assessment of Adult Competencies (PIAAC) demonstrate that adults who use cognitive skills (literacy, numeracy, and technology-related) more frequently exhibit higher decision-making, management, and civic participation both at work and beyond. For example, professionals in healthcare, STEM and social care exhibit stronger transfer of reflection, empathy, and risk assessment into personal decision-making (Eraut, 2004; Illeris, 2011), while educators demonstrate higher reflective practices that spill over into family and social contexts (Korthagen, 2010). In contrast, routine-based sectors such as manufacturing, retail, culinary/food sector, and clerical work offer fewer

opportunities for reflection and adaptive learning (Carbonell et al., 2014), which can limit WBL to job-specific outcomes and hinder broader cognitive transfer.

Despite growing evidence on the importance of workplace learning, a critical gap remains in understanding how learning acquired at work translates into broader cognitive development and real-life decision-making (Smith, 2003). Existing studies have primarily examined WBL as a form of professional training rather than as a catalyst for sustained adult cognitive growth or life-wide learning. Moreover, sectoral variability, where cognitively demanding fields such as healthcare and STEM show higher transfer rates (Castillo et al., 2018) than routine-based occupations, highlights the need to investigate the contextual mechanisms that enable or constrain this transfer. The limited evidence on how WBL contributes to literacy, numeracy, and adaptive problem-solving underscores the absence of an integrated model linking work experience and cognitive development (Windisch, 2015).

To address this gap, this study aims to develop an empirically grounded, AI-informed framework that first tests the existence of a reinforcing nexus between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) empirically. The framework then explains how workplace experiences actively strengthen cognitive growth, adaptability, and lifelong learning capacity across diverse occupational sectors.

Problem Statement

Literature indicates that the reciprocal process through which workplace learning experiences enhance cognitive growth and cognitive resources improve workplace learning remains weak and uneven across sectors and socio-demographic groups (Boud & Garrick, 1999; Eraut, 2004; OECD, 2019). While WBL environments are assumed to foster adult cognitive development, many adults fail to transfer what they learn in the workplace to new or complex contexts,

resulting in limited cognitive adaptability, problem-solving, and metacognitive growth (Kolb, 2015; Mezirow, 1997; Lave & Wenger, 1991). This weak transfer loop often arises from fragmented workplace learning cultures, limited opportunities for reflection-in-action, and insufficient institutional support for continuing cognitive engagement (Schön, 1983; Billett, 2011).

Consequently, adults may demonstrate short-term skill acquisition but lack the more profound cognitive restructuring and adaptive expertise necessary for sustained learning, innovation, and decision-making in dynamic work environments. This disconnect also constrains organizations' capacity for knowledge creation and undermines lifelong learning systems at the societal level.

The research problem for this study, therefore, centers on understanding primarily two things: (1) if there exists a measurable association between WBL-ACD dimensions, and if so, (2) how workplace experiences actively strengthen cognitive growth, adaptability, and lifelong learning capacity and vice versa. Addressing this problem requires analyzing not only the cognitive mechanisms (reflection and feedback, self-efficacy, skill use, and metacognitive awareness) that mediate this relationship, but also the enabling or constraining structural and socio-demographic factors.

Purpose of Research

This study pursues a multifaceted purpose, namely, to determine whether there exists a symbiotic, mutually reinforcing relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). Employing AI-informed modeling, this study also aims to examine the nature, direction, and strength of the proposed WBL-ACD Nexus and to identify workplace-learning strategies associated with favorable cognitive outcomes. This dual analytic

strategy integrates empirical evidence with predictive modeling with AI-informed static policy optimization to investigate potential reciprocal pathways between WBL-ACD and to examine their implications for lifelong learning and adaptive decision-making across personal and professional domains.

Conceptual Framework

In this study, the *Symbiotic WBL-ACD Nexus* is a synthesis that conceptualizes WBL and ACD as dynamically interdependent processes, in which WBL experiences catalyze cognitive growth and ACD capacities enhance WBL experiences. This symbiotic nexus proposes a dynamic feedback system in which WBL and ACD co-evolve through experiential, reflective, and transfer-based processes. It integrates the following elements as layers in the framework:

1. Affordances Layer of Work-Based Learning (Captures what work makes available for learning)
2. Mechanism Layer (Captures how WBL becomes cognitive change through the structural pathways estimated by the SEM, including the reflection mediator)
3. Outcomes Layer of Adult Cognitive Development (Captures the transferable cognitive capacities: literacy, numeracy, and adaptive problem solving)
4. Conditioning Layer comprising a) Structural Conditioning of WBL Affordances (Control Layer) that captures adults' access to and quality of workplace-learning opportunities. Its theoretical purpose is to recognize that learning affordances are partly produced by the organization and structure of work. Workers may therefore encounter different opportunities for complex tasks, autonomy, technology use, collaboration, or workplace learning because of the environments in which they work and b) Covariates (Exogenous

Controls) that represent the measured individual-level characteristics included in the statistical models: Age, Gender (gender_r), Educational Attainment (edcat6_tc1), self-reported health status (i2_Q03), and Immigration Status (imgenc2). These variables were included as exogenous controls to account for systematic differences that may be associated with both workplace-learning opportunities and adult cognitive outcomes.

5. Bidirectional Association and Policy Optimization Layer (Captures the bidirectional association between WBL and ACD identified through the simultaneous equation models and translates these empirical relationships into SEM-informed static policy optimization to identify workplace-learning actions associated with the highest expected cognitive outcomes across observed WBL-ACD states.)

At its core, the symbiotic nexus of WBL-ACD posits that:

1. WBL - ACD: Workplace learning enhances literacy, numeracy, and adaptive reasoning through problem-solving and reflection.
2. ACD -WBL: Stronger cognitive foundations enable deeper engagement, creativity, and reflection in workplace learning.
3. Bidirectional Reinforcement: These two processes form a mutually reinforcing loop, where workplace experience refines cognition, and cognitive growth improves work-based learning.

This looped interaction defines the WBL-ACD nexus as symbiotic (mutually beneficial) and reciprocal (bidirectional).

Research Questions and Hypotheses

This study is guided by two core research questions and corresponding hypotheses. The first question investigates the reciprocal association between adults' engagement in WBL and their cognitive proficiency across three ACD dimensions, literacy, numeracy, and adaptive problem-solving (APS). It hypothesizes that greater engagement in WBL is associated with stronger cognitive proficiency and that stronger cognitive proficiency, in turn, is associated with greater engagement in WBL, reflecting a potentially mutually reinforcing relationship. The second question examines which workplace-learning strategies are associated with more favorable ACD outcomes across different WBL-ACD states. Specifically, the analysis compares training, digital learning, collaborative learning, blended high-WBL engagement, and no extra support using a SEM-informed static policy optimization framework. It is hypothesized that the relative value of these workplace-learning strategies will vary across WBL-ACD states and cognitive domains, indicating that different learning strategies may be more strongly associated with favorable literacy, numeracy, and APS outcomes for adults with different WBL and ACD profiles. Reflection on improving work organization and processes is additionally examined as a mediating mechanism within the structural modeling framework.

Research Design

Because this study aims to examine hypothesized relationships between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) using measurable indicators, it adopts a quantitative research approach. This study adopts a quasi-experimental, simulation-augmented predictive modeling design that combines a family of Structural Equation Modeling (SEM) with static policy optimization to examine the bidirectional association between WBL and ACD using observational cross-sectional data. SEM provides a flexible framework for estimating

simultaneous structural relationships among workplace learning, cognitive development, and reflection while accounting for measurement error and complex interdependencies (Bollen, 1989). Building on these structural estimates, SEM-informed static policy optimization evaluates alternative workplace-learning actions across observed WBL-ACD states to identify the actions associated with the highest expected cognitive outcomes. Unlike dynamic reinforcement learning approaches, the policy optimization does not model transitions over time or iterative updating. Instead, it uses empirically observed state-action outcomes to estimate optimal static policies. Together, these complementary methods strengthen the interpretation of the structural relationships while extending the analysis to provide evidence-based recommendations for workplace-learning strategies associated with improved literacy, numeracy, and adaptive problem-solving outcomes. This integrated approach offers a rigorous framework for understanding the interplay between workplace learning and adult cognitive development and for informing evidence-based workplace learning interventions.

The data source for the study is the 2023 cycle of the Programme for the International Assessment of Adult Competencies (PIAAC). It is an OECD-led international survey assessing adults' key cognitive and workplace skills. It measures literacy, numeracy, and adaptive problem-solving (APS) among adults aged 16–65 across more than 30 participating countries. Using a stratified probability sample representative of national adult populations, approximately 5,000 respondents per country completed computer-based or paper-based assessments, accompanied by detailed background questionnaires. The 2023 cycle updated prior domains (literacy and numeracy) and introduced APS, focusing on adaptability and cognition in digital contexts, thereby capturing how adults apply knowledge and skills in real-life problem-solving situations.

In this study, Work-Based Learning (WBL) and Adult Cognitive Development (ACD) are examined within a simultaneous equation framework in which each construct serves as both an exogenous and an endogenous variable depending on the structural pathway being estimated. WBL is represented as a latent construct measured through learning at work, ICT use at work, and influence over work activities. ACD is assessed separately across three domains using PIAAC plausible values for literacy, numeracy, and adaptive problem-solving (APS). Reflection, operationalized as involvement in improving work organization or work processes, is examined as a mediating mechanism linking workplace learning and cognitive development. Demographic and employment characteristics, including age, gender, educational attainment, and immigration status, are incorporated as exogenous control variables to account for structural differences in workplace-learning opportunities and cognitive outcomes.

To ensure the credibility, stability, and interpretability of the findings, this study applies a structured set of diagnostic procedures across two complementary analytical approaches: SEM and SEM-informed static policy optimization. Diagnostics and evaluation criteria are specified a priori to avoid post hoc justification and to promote transparent and reproducible inference. For the SEM analyses, model adequacy is evaluated using established fit indices, standardized parameter estimates, convergence diagnostics, and robustness analyses. The SEM-informed static policy optimization is evaluated through expected reward comparisons, bootstrap policy stability analyses, and comparative action-effect estimates, providing evidence for the consistency and practical robustness of the recommended workplace-learning actions.

Overall, the research design represents a rigorous and innovative methodological toolkit for generating evidence-based insights into the symbiotic WBL–ACD nexus, illuminating how adults acquire and apply workplace learning while interacting with the core dimensions of

cognitive development. The quasi-experimental, simulation-augmented predictive modeling design uniquely integrates the strengths of both causal inference and adaptive simulation approaches. This integrated methodological design offers several advantages: (1) it enhances external validity and predictive accuracy, as quasi-experimental methods provide empirical grounding while simulations generate forward-looking estimates, yielding more generalizable findings; (2) it ensures replicability through systematic modeling of empirical and simulated data; (3) it improves internal validity by employing structured selection and control of variables; (4) it enables the evaluation of both observed causal impacts and projected long-term scenarios, thereby supporting evidence-informed policymaking; and (5) it captures micro- and macro-level dynamics of learning and cognition within real-world contexts by linking individual-level behavioral data (e.g., literacy, numeracy, and adaptive problem-solving) with system-level influences such as sectoral conditions, technological exposure, and learning ecosystems. This multi-layered capacity makes this methodological design particularly suited to understanding how WBL and cognitive development co-evolve within complex, real-world environments.

Significance of Study

Theoretical Significance

The WBL–ACD nexus integrates principles from experiential learning (Kolb, 2015), transformative learning (Mezirow, 1997), and situated learning theories (Lave & Wenger, 1991), along with metacognitive theory (Flavell, 1979), to frame adult learning as a dynamic, cyclical process. It bridges micro-level cognition and macro-level workplace contexts by showing how reflection and metacognition interact with organizational learning environments. The framework models reciprocal association, asserting that cognitive development both arises from and enhances work-based learning, creating feedback-driven, self-reinforcing learning ecology.

Empirical Significance

The findings of this study are significant for advancing interdisciplinary research on adult learning, cognitive development, and leadership studies, while expanding the analytical scope of PIAAC data. Very little research has explored the potential of adult learning within the framework of the Sustainable Development Goals (SDGs), particularly its role in promoting SDG 4: Quality Education and addressing global challenges such as workforce adaptability. By modeling the WBL–ACD nexus, this study contributes new scientific insights into whether there is any measurable and reinforcing association between WBL-ACD and how adults' workplace learning experiences reinforce cognitive growth across five major workplace sectors. Moreover, the study provides a methodological and conceptual foundation for leveraging the new PIAAC 2023 cycle, offering updated evidence on adult skills, sectoral learning ecosystems, and the cognitive returns of work-based learning. These findings underscore the continued global relevance of PIAAC and highlight the need for similar large-scale, context-sensitive data assessments in regions facing acute skill inequity, thereby bridging research, policy, and practice in advancing adult learning for sustainable development.

Moreover, the study presents a comprehensive analytical framework to explain differences in adult learning outcomes across various sectors. Linking underlying mechanisms of WBL indicators, such as reflection, feedback, and skill use, to ACD dimensions like literacy, numeracy, and adaptive problem-solving enables the precise modeling of learning trajectories. Integrating SEM and static policy optimization further supports longitudinal and adaptive analysis.

Policy and Practice Significance

The study aligns with global education and workforce development priorities by operationalizing SDG 4.4, which emphasizes the development of skills for employment and lifelong learning. It provides evidence-based insights to inform the development of adult education and workforce policies, concurrently informing the design of more effective WBL programs that improve both productivity and learning capacity. Additionally, it advances evaluation practice by encouraging the measurement of cognitive growth, rather than mere participation, shifting evaluation systems toward a developmental, impact-oriented approach that supports sustained, lifelong learning outcomes.

Societal Significance

The proposed symbiotic and mutually reinforcing WBL–ACD nexus helps close the persistent "knowing–doing gap" in the literature by explaining why workplace learning often fails to transfer into real-world decisions. It promotes cognitive equity by positioning workplace learning as a key avenue for cognitive empowerment, ensuring broader access to meaningful learning opportunities that reduce skill and knowledge disparities. Moreover, it strengthens resilience and adaptability, fostering adults' capacity to learn, unlearn, and relearn in the face of technological and economic change. Together, these outcomes advance lifelong learning and enhance adults' ability to navigate complex, evolving real-world environments effectively.

Limitations/ Delimitations of the Study

While this study makes a novel contribution by examining the relationship and modeling the relationship between WBL and ACD, several limitations should be acknowledged. First, the analysis is based on cross-sectional data from the PIAAC 2023 cycle, which restricts the ability to draw strong causal inferences about temporal changes in learning and cognition. Although

integrating Simultaneous Equation Modeling (SEM) and static policy optimization enables partial estimation of reciprocal and adaptive dynamics, accurately tracking adult learning trajectories over time remains beyond the scope of the dataset.

Second, PIAAC's self-reported WBL indicators (e.g., participation in non-formal training, skill use, reflection) may be subject to recall and social desirability biases, which limit the precision in measuring workplace learning processes. Similarly, the use of plausible values (PVs) for literacy, numeracy, and adaptive problem-solving introduces measurement error and imputation uncertainty, requiring cautious interpretation of effect sizes and relationships. Third, the reciprocal SEMs exhibited estimation instability, indicating that the magnitude of simultaneous reciprocal effects should be interpreted cautiously.

Fourth, the static policy optimization framework evaluates interventions within observed WBL–ACD states and therefore does not model how individuals transition between states over time. Consequently, optimized policies represent evidence-informed recommendations based on observed cross-sectional relationships rather than dynamic learning trajectories. Finally, the analyses were conducted using the United States PIAAC sample, and future studies should examine whether similar patterns emerge across other national contexts.

Despite these limitations, the study provides an empirically grounded, theoretically integrated, and methodologically innovative framework for understanding how adults learn, transfer, and adapt knowledge across work and life domains, offering a strong foundation for future longitudinal, cross-cultural, and mixed-methods research.

Chapter Summary

This chapter explored the conceptual, empirical, and methodological foundations of the proposed study, which investigates the symbiotic relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). It addressed the persistent "knowing–doing gap," where adults often struggle to apply workplace-acquired skills to real-life decision-making, and positioned this challenge within global goals for lifelong learning and skill development. Drawing on the OECD's 2023 Programme for the International Assessment of Adult Competencies (PIAAC), the chapter outlined how literacy, numeracy, and adaptive problem-solving (APS) serve as key indicators of ACD.

This study is guided by a conceptual framework that views work-based learning (WBL) and adult cognitive development (ACD) as a dynamic, reciprocal system. WBL is conceptualized as a learning ecology in which workplace affordances activate learning mechanisms (e.g., reflection, metacognitive regulation, learning agency, and sustained skill use) that mediate the relationship between work experience and cognitive development. ACD is expressed as transferable competencies, including literacy, numeracy, and adaptive problem solving, reflecting both skill acquisition and cognitive flexibility. The framework further recognizes that individual and structural conditions shape access to learning and the strength of these mechanisms, while cognitive development itself feeds back over time to enable richer workplace learning opportunities.

The research adopts a quasi-experimental, simulation-augmented predictive modeling design that integrates Simultaneous Equation Modeling (SEM) and static policy optimization. This dual-method approach captures both causal pathways and adaptive learning dynamics. Work-Based Learning (WBL) is represented by learning at work, ICT use at work, and influence

over work activities, and is modeled in simultaneous equation models as both a predictor and an outcome of Adult Cognitive Development (ACD). Reflection, operationalized as involvement in improving work organization or work processes, is examined as a mediating mechanism linking WBL and ACD. Demographic and employment characteristics, including age, gender, educational attainment, and immigration status, are incorporated as exogenous control variables to account for structural differences in workplace learning opportunities and cognitive outcomes.

The chapter proposes testing the existence and strength of bidirectional WBL–ACD linkages and validating these through static policy optimization. By combining empirical modeling with policy optimization, the chapter positions WBL as both a catalyst and beneficiary of adult cognitive growth. This framework provides a foundation for advancing theory, policy, and practice on lifelong learning, demonstrating how workplace experiences can cultivate enduring cognitive adaptability and informed decision-making in complex, evolving environments.

Definition of Terms

Table 1-1 Terms and Their Definitions

Key Terms/Concepts	Definitions	References
1. Adult Cognitive Development (ACD)	ACD encompasses scores from adult literacy, numeracy, and adaptive problem-solving skills (APS) and are considered as core domains.	OECD, 2013; 2019
2. Work-based Learning (WBL)	A comprehensive and multidimensional pedagogical strategy that is typically supported by a number of learning theories and is aimed at deriving job-related learning to enhance employability, skills, and career readiness.	Raelin, 2008
3. Literacy	It incorporates comprehension, interpretation, and use of written texts, fundamental to learning and decision-making	OECD, 2025

4.	Numeracy	It involves the ability to interpret, use, and apply mathematical concepts centrally to reasoning and quantitative problem-solving.	OECD, 2025
5.	Adaptive Problem-Solving skills (APS)	The capacity of an individual to achieve one's goal in a dynamic situation in which a method of solution is not immediately available. It requires individuals to engage both cognitively and metacognitively.	OECD, 2025
6.	Sustainable Development Goals (SDG)	It's the universal call to action to end poverty, protect the planet, and ensure that all people enjoy peace and prosperity by 2030" (United Nations Development Program.	UNDP, 2024
7.	Symbiotic relationship	A symbiotic relationship is a sustained and interdependent association between two entities in which both derive mutual benefit, contributing to each other's growth and adaptation.	Bronstein, 2015
8.	The Program for the International Assessment of Adult Competencies (PIAAC)	It is the only household international large-scale dataset that talks about the cognitive and workplace skills of adults that are needed for their participation in 21st-century society.	Soroui, 2024
9.	Descriptive statistics	It is a statistical tool to summarize, organize, and describe the main features of a dataset**.**	Gravetter & Wallnau, 2021
10.	Dependent Variable	A dependent variable is the outcome whose variation you aim to explain.	Kline, 2016
11.	Endogenous Variable	In SEM and causal modeling, a dependent variable is called endogenous, meaning its value is determined within the system by other variables in the model.	Kline, 2016
12.	Independent Variable	The independent variable is the explanatory factor that predicts or influences the dependent variable.	Kline, 2016
13.	Mediator Variable	It explains how or why an independent variable influences a dependent variable.	Baron & Kenny, 1986
14.	Exogenous Variable	It originates outside the model and is not explained by other variables. All exogenous variables are independent variables; however, the reverse is not true.	Kline, 2016
15.	Moderator Variable	It influences the strength or direction of the relationship between an independent (predictor) and a dependent (outcome) variable.	Baron & Kenny, 1986
16.	Control Variable	This variable is not the main focus of a study but is accounted for or held constant because it may influence the relationship between independent and dependent variables.	Seltman, 2018

17.	Causal Estimation	It is a process of quantifying the cause-and-effect relationship between variables—specifically, determining how much change in an independent variable (cause) leads to a change in a dependent variable (effect) while accounting for confounding factors.	Pearl, 2009
18.	Q learning simulation model	It's a model-free reinforcement learning method where there is an agent who learns from an action-value Q (*s, a*) that estimates the expected cumulative reward for taking a certain action *a* in state *s* and thereby determining the most appropriate policy direction. The process of learning is driven by iterative updates using sampled transitions. In this process, the exact probabilities of moving from one state to another (transition process) in a given action are completely unknown.	Sutton & Barto, 2018
19.	Simultaneous Equation Modeling	It is a statistical technique used to analyze complex causal relationships among multiple interdependent variables within a single analytical framework, accounting for reciprocal relationships.	Bollen, 1989
20.	Machine learning tools	These are tools that help computer systems to predict outcomes more accurately using a variety of algorithms. Some examples of machine learning algorithms are linear regression, random forests, and logistic regression. They can perform a variety of tasks, including forecasting, analyzing the effectiveness of an outcome, risk assessments, prevents risk of overfitting in data, etc.	Foote, 2022
21.	Kolb's experiential theory	It explains how adults are able to convert work experience to skills through the repetitive process of *action and reflection*.	Kolb, 1984
22.	Mezirow's transformational learning	It digs deeper into why and when adults' cognitive perspectives transform because of new, complex, and /or challenging experiences.	Meizrow, 1991
23.	Metacognitive theory	It describes how adults optimize their learning process when they come across complex work.	Flavell, 1979
24.	Situational learning theory	Learning is most effective when it is embedded in real-world tasks, social interaction, and cultural context, rather than isolated classroom settings.	Lave & Wenger, 1991

25. Static Policy Optimization	Static policy optimization is a decision-analytic approach that identifies the workplace-learning action associated with the highest expected outcome for each observed state without modeling sequential decision-making or changes over time.	Murphy, 2003

Chapter 2 - Literature Review

Introduction

This chapter provides a comprehensive overview of the current understanding of the relationship between WBL and ACD as reflected in the literature and highlights its crucial role in promoting more informed decision-making among adults. It expands on WBL features relevant to ACD and ACD's contribution to WBL, thereby providing a solid foundation for understanding how strengthening the nexus between the two can promote more effective learning practices. Key concepts related to WBL and ACD are discussed, shedding light on the theoretical perspectives underpinning this connection. The symbiotic WBL-ACD framework is reviewed in light of the literature base. Finally, how this framework behaves based on workplace sectors is discussed to shed light on emerging patterns and contexts.

Having outlined this chapter, it is vital to clarify the meaning of WBL. While WBL is a widely recognized, valuable approach to adult learning, its definition and scope remain the subject of debate. Scholars in the field have presented varied interpretations, ranging from structured, curriculum-aligned instruction to more expansive notions of experiential and situated learning. The following sections clarify WBL in the context of supporting the claim of whether

or not there is a measurable, mutually reinforcing WBL-ACD nexus, frame the subsequent analysis, and build consistency in understanding the nature of the nexus.

Work-Based Learning

WBL is defined as a comprehensive pedagogical strategy that integrates more structured, curriculum-aligned instruction, exposing learners to practical or simulated work experiences (Little & Harvey, 2006; Billet, 2011). Guile & Griffiths (2001) elaborate on WBL's definition by integrating experiential learning into the academic curriculum, emphasizing the developmental potential of workplace learning. The philosophy of WBL, besides encompassing the practical or real-world work experiences, stresses reflection and knowledge transfer, and how these experiences at the workplace enrich conceptual understanding (Raelin, 2008; Tynjälä, 2008).

One thing to note here is that WBL usually, but not always, means job-related learning. The traditional definition, used in policy, education, and workforce development contexts, relates to structured learning that occurs through participation in or work-like activities (e.g., internships, apprenticeships, cooperative education, job shadowing, employer-provided training, or on-the-job learning). However, WBL, in a broader sense, could also be defined as learning derived from one's own work experience, leading to ACD growth (Boud & Solomon, 2001; Raelin, 2008). In this study, WBL reflects job-related learning, aiming to enhance employability, skills, and career readiness.

Therefore, WBL is not a formal theory per se, but rather a multidimensional pedagogical framework that is typically supported by more established learning theories, including but not limited to Kolb's experiential learning, Mezirow's transformative learning, Flavell's metacognitive theory, and Lave and Wenger's situated learning (Raelin, 2008; Billett, 2011;

Garnett, 2016; Malloch et al., 2011). The following sub-sections describe the commonly observed dimensions of WBL.

Dimensions of WBL

WBL has been conceptualized differently by different scholars across the fields. Seven key dimensions have recurred in the literature base: (1) Experiential or practical; (2) Reflective; (3) Collaborative or social; (4) Knowledge integration; (5) Skill development; (6) Contextual; and (7) Lifelong orientation.

Experiential or practical dimension

The experiential or practical dimension of WBL emphasizes learning through direct engagement in work tasks and projects (Eraut, 2004). In practical contexts, it accentuates the principle of "learning by doing" (Kolb, 1984; Tynjälä, 2013). Some examples of tasks that involve the experiential dimension include apprenticeships (Lave & Wenger, 1991; Billet, 2011), internships, and job shadowing.

Reflective dimension

The reflective dimension of WBL enables the mechanism for transferring experience into learning (Raelin, 2008; Tynjälä, 2008). Systematic episodes of reflection at the workplace deepen understanding and facilitate knowledge transfer (Tynjälä, 2008). Examples include self-reflection, peer dialogue, and supervisor feedback.

Collaborative or social dimension

The collaborative or social dimension of WBL supports learning through interaction with members of the professional community (e.g., colleagues, mentors), building stronger communication networks, teamwork, and situated knowledge (Lave & Wenger, 1991; Fuller &

Unwin, 2004; Nicolini et al., 2022; Zamiri & Esmaeili,2024). Some examples for this type of dimension include social interaction, mentoring, and peer learning (Malloch et.al., 2011).

Knowledge dimension

The knowledge dimension of WBL establishes the link between theory or concepts and workplace practice (Guile & Griffiths, 2001). An ideal example would be any curriculum-aligned WBL that warrants workplace experiences to underline academic or vocational content (Garnett, 2016).

Skill development dimension

The skill development dimension of WBL encompasses both domain-specific and transferable soft skills, which can be acquired through technical, professional, and employability skills (Illeris, 2011) in various problem-solving, adaptability, and digital tasks (OECD, 2019).

Contextual dimension

The contextual dimension of WBL incorporates learning in real-life or simulated work settings. Authentic tasks like on-the-job training, internships, problem-based learning, apprenticeship, and menu planning make learning more meaningful and transferable to real-life decision-making (Tynjälä, 2013; Billett, 2011)

Lifelong orientation dimension

As the name suggests, the lifelong dimension of WBL instills a culture of continuous skill upgrading in adults, fostering persistence in ACD. Professional development, workplace training, and upskilling, as well as reskilling, are typical examples of WBL that encompass lifelong learning (Illeris, 2014; OECD, 2023). This study considers WBL experiences across these various dimensions. Given its multidimensional nature, WBL in workplaces makes a significant contribution to the growth of ACD.

WBL's contribution to ACD

Some literature indicate that WBL contributes to ACD through practice (e.g., repetitive tasks like reading safety manuals, calculating budgets, which strengthen fluency, accuracy, and automaticity in core ACD skills), context (e.g., real-life contextual learning like applying numeracy in logistics planning tasks links abstract concepts with applied practice tends to embed knowledge more securely), reflection (e.g., debriefing tasks by healthcare professionals to refine decision-making is a form of reflection task that develops metacognition, strengthening ACD outcomes), collaboration (e.g., team-based problem-solving tasks involves social learning processes that expand critical thinking, adaptability, and reasoning), adaptability (e.g., adapting to workflow after a new technology adoption, which requires adaptive problem solving and resilience that strengthens ACD flexibility), and lifelong learning (e.g., ongoing professional development tasks boosts continuous learning and reskilling that supports long-term ACD), by creating a mutually reinforcing cycle where cognitive skills act as both enabling and strengthening factors through workplace learning (Tynjälä, 2008; Raelin, 2008). These are underlying critical mechanisms that govern WBL's contribution to the growth of ACD.

Mechanism Involved in the Contribution

WBL influences ACD when there is scope for reflection, collaboration, and problem-solving tasks at the workplace (Raelin, 2008; OECD, 2019), rather than repetitive tasks. Features like practice and feedback, reflection and collaboration, and complex technology-rich tasks further impact immediate cognitive outcomes and enhance the transferability of learning (Winne & Hadwin, 2010).

Practice and Feedback

Continuous and repeated cycles of practice and feedback from WBL opportunities (e.g., trainings, internships) drive ACD domains in an adult's regular activities by providing reflective adjustments that ensure cognitive growth and improved decision-making ability (Ericsson et al., 1993; Raelin, 2008). Both structured practice and feedback-rich environments enhance skill use and reflection (Tynjälä, 2008; Billett, 2011; Berning et al., 2024; Maqsood et al., 2025).

Reflection and Collaboration

In the WBL-ACD nexus, reflection as an internal process and collaboration as a social process act as pedagogical strategies that are very critical learning tools and directly contribute to promoting cognitive growth and lifelong learning (Raelin, 2008). The process of reflection is transformational in nature, which turns experiences into learning outcomes (Boud et al., 1985; Mezirow, 1997), supporting higher stages of adult cognitive development. Eraut (2004) showed that both reflection and collaboration in an informal WBL environment drive ACD and decision-making.

Digital Tool Use and Task Complexity

The use of digital tools while engaging with workplace technologies enhances problem-solving skills**,** while also promoting literacy through digital texts and numeracy through quantitative tasks (Sakurai & Goos, 2023). Task complexity, on the other hand, builds relatively more cognitive growth by providing increased resources than regular technical tasks, resulting in improved reasoning and adaptability skills (Ericksson, 2006; Billett, 2014). On combining both digital tool use and participation in complex workplace tasks, an adult gains deeper cognitive development and skills transfer (Tynjälä, 2013).

Grounding in the pedagogical foundations of WBL, examining how adult learning outcomes can be analytically assessed is crucial. WBL guides adults' learning and development

through workplace experiences, and large-scale assessments such as PIAAC can reveal what skills are strengthened through this process. By focusing on the core dimensions of ACD (literacy, numeracy, and APS), PIAAC provides a realistic basis for examining the extent to which WBL contributes to ACD outcomes across varying contexts.

Adult Cognitive Development (ACD): Literacy, Numeracy, APS

Adult Cognitive Development (ACD) encompasses adult literacy, numeracy, and adaptive problem-solving skills (APS) and are considered as the core domains of cognitive development. The OECD-PIAAC 2023 report identifies literacy, numeracy, and APS as the three primary skill domains for measuring ACD (OECD, 2023).

Core Dimensions of ACD

Literacy

Literacy is defined as the ability of adults to understand, evaluate, use, and engage with written texts to participate in societal actions, achieve their goals, and acquire their knowledge and potential (OECD, 2019). The content incorporated a variety of texts (e.g., continuous and non-continuous texts, mixed and multiple), creating a range of contexts in domains including work, personal, society and community, and education and training. The intent is to measure the cognitive capabilities of adults, specifically their ability to access and identify information, relate pieces of information from texts to one another, and evaluate and reflect on the information presented in the texts (OECD, 2019).

Numeracy

Numeracy is the ability to access, use, interpret, and communicate various numerical information to solve regular mathematical problems in adult life. To assess numerical capability, the PIAAC survey engages respondents in mathematical content that includes quantity and

number, dimensions and shapes, patterns, relationships and change, visual displays, data and chance, technology-based displays, and objects and pictures encompassing multiple cognitive strategies (e.g., interpretation, evaluation, and analyzing) and contexts (work and personal, society and community level).

Adaptive Problem-Solving (APS)

APS proficiency is one of the new additions in the survey. APS replaced PSTRE in the most recent PIAAC cycle two surveys in 2023, shifting the focus to cognition and adaptability, with technology used as a tool rather than a primary focus. However, PSTRE is more technology focused. APS in PIAAC estimates the ability of adults to adapt problem-solving strategies in a more dynamic, uncertain environment that fully utilizes cognitive skills (e.g., reasoning, planning) and metacognitive processes (e.g., monitoring, reflection, adjustments) focusing more on the skill part, with technology as one of the tools (OECD 2019, 2021, 2023; CSO, 2024).

While all three core dimensions of ACD (as measured by PIAAC) discussed above are pivotal outcomes of adult education and training, several research studies indicate that they also act as vital enablers of WBL, contributing to and shaping workplace engagement. Having stronger ACD skill dimensions enables adults to engage more effectively in workplace tasks, reflect more thoroughly on their experiences, and transfer learning across contexts, thereby reinforcing the WBL-ACD nexus (NRC, 2012; Eraut, 2018; Fergusson, 2022; Hommel et al., 2023; Okunlola, 2023).

ACD's contribution to WBL

As discussed in the previous paragraph, ACD lays down the foundation where adults can fully participate in and benefit from WBL. While WBL enriches and strengthens ACD using practice and reflection, stronger ACD dimensions (literacy, numeracy, and APS) enable adults to

engage in WBL more effectively. Several studies indicate that this process is dynamic and reciprocal.

Literacy serves as a catalyst for WBL, enabling adults with stronger literacy skills to better interpret written documents at the workplace (e.g., training manuals and other forms of communications, including digital information). Literacy influences reflection by inducing critical evaluation tendencies among adults (e.g., work-related information, record experiences, sharing knowledge) and engagement by enabling adults to interact with both structured and unstructured training materials at the workplace (Nikou et al., 2022; Muellmann et.al., 2025)

Numeracy enables problem-solving in WBL by supporting adults in interpreting numerical information and applying quantitative reasoning to workplace tasks such as budgeting, quality control, and forecasting. Stronger numeracy skills enhance an adult's confidence and efficiency in workplace problem-solving tasks, strengthening WBL.

APS works as a driver of workplace adaptability among adults, empowering them to respond to novel, uncertain, and dynamic work environments. It fosters an element of flexibility toward learning (OECD, 2023). This flexibility supports translation of workplace experiences into broader skills and long-term learning gains. Together, these three core dimensions of ACD, through multiple mechanisms (e.g., foundational cognitive, metacognitive, and psychosocial skills), facilitate WBL experiences among adults.

Mechanism Involved in the Contribution

According to OECD (2019), ACD contributes to WBL by enhancing literacy skills (e.g., information access), numerical comprehension and proficiency (e.g., quantitative reasoning) (Gal et al., 2020), promotes flexible engagement with WBL activities through enhanced APS skills (e.g., adaptability and metacognition) (OECD, 2023), reflection (e.g., transfer knowledge)

(Tynjälä, 2008), and. self-efficacy (e.g., engagement) (Bandura, 1997). Combinedly, all these mechanisms make sure that stronger ACD foundations have a profound positive impact on workplace learning, making it more meaningful, effective, and transferable.

Thus, the arguments above show how ACD contributes to WBL by providing the ACD foundations for engagement, while WBL, in turn, strengthens and expands those skills through realistic practice. This relationship is reciprocal, more dynamic, and mutually reinforcing, paving the way for effective transfer of learning. This transfer of learning enables adults to apply workplace-derived knowledge and skills to complex real-life decision-making

Conceptual Framework

Symbiotic WBL-ACD Nexus Framework

Work-based learning environments provide affordances that open up possibilities for actions or learning that an environment offers to a learner (Billett, 2001), and participation opportunities (situated learning theory) that generate experience - feedback cycles (experiential learning theory) (Billett, 2001, 2016; Eraut, 2004; Kolb, 2015; Lave &Wenger, 1991). These experiences translate into cognitive gains when adults engage in reflective sense-making, critical reflection, and metacognitive regulation, supported by self-efficacy and sustained skill use (Bandura, 1997; Flavell, 1979; Mezirow, 1997; Raelin, 2008; Schon, 1983). Cognitive outcomes include both domain competencies and adaptive problem-solving capacity (OED, 2016, 2019; Reder, 2020). The strength of these pathways varies by digital readiness, education, age, and gender (Desjardins & Rubenson, 2013; Green & Gallie, 2020; OECD, 2021), while sectoral and socio-economic conditions shape access and baseline opportunity structures (Bills, 2016; Rubenson & Desjardins, 2009). Over time, cognitive gains feed back into improved capacity to engage in

more complex work and richer learning opportunities (Heckman & Reder, 2014; Reder, 2014), reinforcing the WBL-ACD cycle.

Building on the concepts of WBL and ACD dimensions stated above, a symbiotic WBL-ACD framework is proposed to guide this research by conceptualizing adult learning as a dynamic, mutually reinforcing relationship between WBL and ACD. This proposed reinforcing nexus is established when WBL provides authentic, experiential, and reflective opportunities that catalyze the growth of ACD core dimensions (literacy, numeracy, and APS). In turn, the strengthened ACD enhances an adult’ s ability to fully engage and immerse in, benefit from, and transfer workplace learning into broader and more practical life contexts (Raelin, 2008; Illeris, 2011). The framework is composed of three core components and builds on some assumptions that are described in the following sections.

Core Components and Assumptions

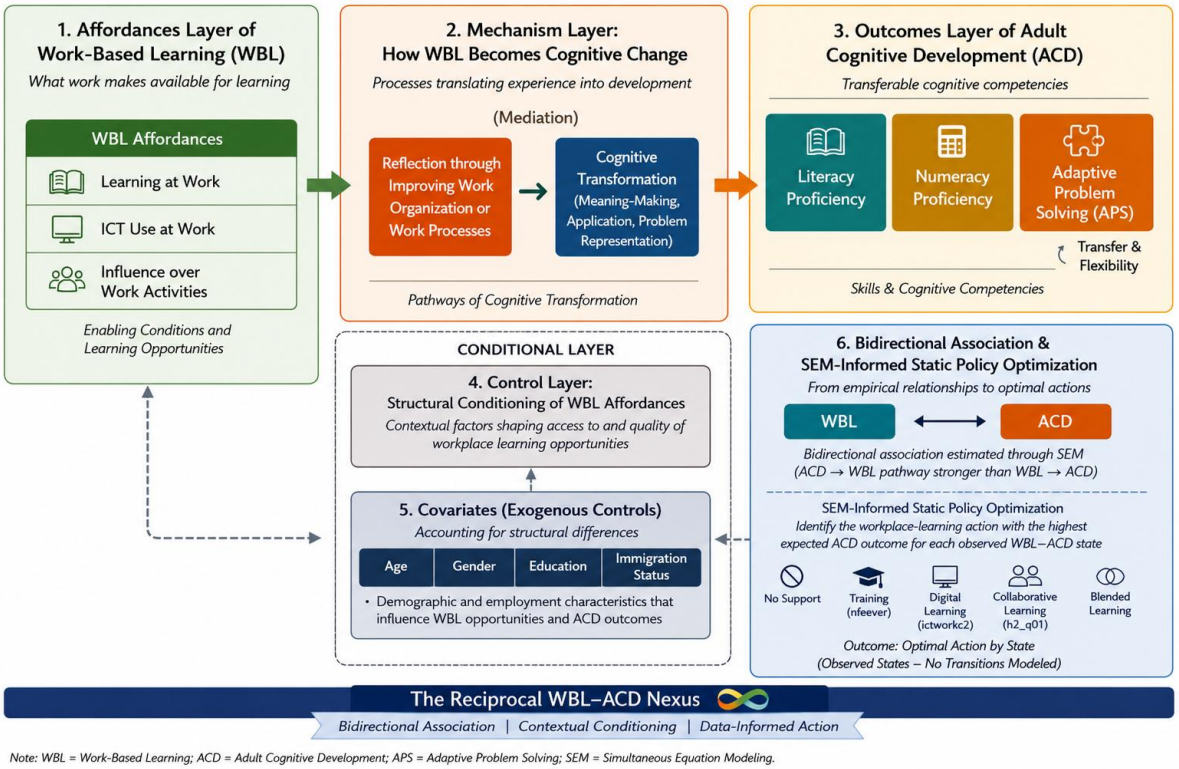
The core components include: (1) Affordances Layer of Work-Based Learning (WBL): What work makes available for learning; (2) Mechanism Layer: How WBL Becomes Cognitive Change Processes translating experience into development; (3) Outcomes Layer of Adult Cognitive Development (ACD) Transferable cognitive competencies, (4) Moderation Layer: Conditioning the Strength of the Mechanism Layer Why the same WBL yields different outcomes, (5) Control Layer: Structural Conditioning Shaping WBL Affordances Contextual placement and access to learning, and (6) Reciprocal Feedback Layer ACD reinforcing future WBL affordances and mechanisms.

The majority of scholars and researchers in the field assume WBL as a process and treat it as an input that facilitates ACD (Raelin, 2008; OECD, 2013). With this assumption, an adult who engages in a WBL task at the workplace is supposed to develop literacy, numeracy, and

APS skills, which will strengthen daily decision-making and lifelong learning. However, the reverse direction of associations is less often used, but logically forms a strong case, where WBL is treated as an outcome (OECD, 2013; Boeren, 2017). Research studies have shown that adults with higher ACD scores actively seek out more WBL opportunities and succeed in them (OECD, 2013; Ioannidou & Desjardins, 2020).

The current study makes a dynamic or reciprocal model assumption for the WBL-ACD nexus (Figure 2.1) - symbiotic WBL-ACD nexus, which states that WBL strengthens ACD using situated experience and reflection practices, and ACD enables WBL when adults have a higher level of skills, promoting more engagement and application of WBL opportunities at the workplace (Billett, 2001; Illeris, 2011; Evans et al., 2011; OECD, 2019).

Figure 2-1 Conceptual Framework describing the dynamic Model Assumptions for WBL-ACD Nexus.



Note.

- The figure is color-coded to distinguish the conceptual and analytical components of the WBL-ACD Framework: Green: Affordances Layer of Work-Based Learning; Orange: Mechanism Layer; Yellow: Outcomes Layer of Adult Cognitive Development; Gray: Control Layer representing structural conditioning of WBL affordances; Blue: Covariates (Exogenous Controls) Layer; and Light Blue: Bidirectional Association and SEM-Informed Static Policy Optimization Layer. The Control Layer and Covariates Layer are jointly enclosed within the Conditional Layer, reflecting the broader structural and individual conditions within which the WBL-ACD relationship occurs. The Control Layer represents theoretically relevant contextual influences that were not directly modeled, whereas the Covariates Layer contains the exogenous characteristics included in the empirical models.
- Arrows indicate the directional and analytical logic of the WBL-ACD Framework:
- Affordances → Mechanisms (solid rightward arrow) indicates that workplace-learning affordances, represented by learning at work, ICT use at work, and influence over work activities, provide opportunities for learning that may be translated into cognitive development through reflection and cognitive transformation.
- Mechanisms → Outcomes (solid rightward arrow) represents the proposed mediation pathway through which reflection related to improving work organization or work processes connects workplace learning with literacy, numeracy, and adaptive problem solving. Empirically, the reflection-related mechanism was associated with literacy and APS, while evidence was weaker for numeracy, indicating a domain-sensitive rather than uniform mediation pathway.
- Conditional Layer encompasses both structural conditioning and modeled exogenous covariates. The Control Layer recognizes that broader contextual characteristics, such as occupational, sectoral, and organizational conditions, may shape access to and the quality of workplace-learning affordances; these contextual influences are conceptual and were not directly estimated as controls in the present models. The Covariates Layer, comprising age, gender, education, and immigration status, represents exogenous characteristics statistically controlled to account for observed differences in WBL opportunities and ACD outcomes. These variables are not modeled as moderators.
- Bidirectional Association (double-headed WBL ↔ ACD arrow) represents the relationship examined through competing SEM specifications. The empirical findings indicate an asymmetric and model-dependent bidirectional association, with the ACD → WBL pathway showing greater robustness than the WBL → ACD pathway.
- SEM-Informed Static Policy Optimization translates the empirical WBL-ACD evidence into state-specific, data-informed action. Model 1 (Forward Recursive Mediation SEM) provides the directional WBL → ACD information used to inform the reward function. Alternative workplace-learning actions are compared within observed WBL-ACD states to identify the action associated with the highest expected ACD outcome. The approach does not model state transitions, longitudinal learning trajectories, or iterative policy updating; therefore, the resulting recommendations represent optimal static actions conditional on observed states rather than dynamic reinforcement-learning policies.

Affordances Layer of Work-Based Learning (WBL)

Affordances are the action possibilities the WBL environment offers an adult in the context of how it can be used (Billet, 2001, 2016; Gibson, 1979). WBL shapes ACD by what work makes available and what adults actually do in practice (Billet, 2004; Felstead et al., 2016). Hence, the proposed WBL-ACD nexus claims that WBL provides the conditions for learning and the opportunities for cognitive exercise (Eraut, 2004; Tynjälä, 2013). Workplace affordances enable participation, but learning only occurs when participation turns into repeated experience–feedback loops (Lave & Wenger, 1991; Wenger, 1998).

Some examples of WBL affordances include task complexity, autonomy/decision latitude, feedback availability, time pressure, role variety, access to tools/technology, supervisor support, peer interaction (Hackman & Oldham, 1976; Karasek & Theorell, 1990; OECD, 2019). Two very relevant mechanisms work in the framework, namely, participation, and experience. The mechanisms of how adults participate and learn is based on concepts borrowed from Flavell's situated theory that includes concepts like learning through legitimate participation, observation, coaching, collaboration, and shared routines within a community of practice (Billet, 2008; Lave & Wenger, 1991). The mechanism of experience is based on conceptual elements from the Kolb's experiential learning theory that include repeated engagement with authentic tasks, creating cycles of doing–feedback–adjustment (Kolb, 1984, 2015; Soderstorm & Bjork, 2015).

Mechanism Layer of how WBL becomes Cognitive Change

This layer is the "engine room" of the framework, representing the processes that convert work experience into cognitive gains (gains in ACD dimensions). The workplace conditions (affordances) do not directly produce cognitive development (Billet, 2001; Eraut, 2004; Tynjälä,

2013). Instead, they activate learning mechanisms. Four key processes involved include reflective processing (Kolb, 1984, 2015; Mezirow, 1997, 2000; Schön, 1983), metacognitive regulation (Flavell, 1979; OECD, 2019; Zimmerman, 2002), self-efficacy and agency (Bandura, 1997; Billet, 2011; Raelin, 2008), and skill use and deliberate cognitive practice (Ericsson et al., 1993; Kolb, 2015; Lave & Wenger, 1991).

WBL affects ACD primarily through these four mechanisms. Task complexity, autonomy, tools, and support (obtained from WBL affordances) enable reflection, metacognition, self-efficacy, and skill use, but do not guarantee them. All four processes are discussed below:

Reflective Practice

This is a key concept from Kolb's experiential learning theory and Mezirow's transformational learning theory (Kolb, 1984, 2015; Mezirow, 1997). It is primarily sense-making after doing the task and involves reflection-in-action and reflection -on-action practices (Schön, 1983). When reflection becomes critical (transformative), it can change frames of reference for adults, not just improve performance (Mezirow, 2000).

Metacognitive regulation

It is a key concept from Flavell's metacognitive theory, where an adult is planning, monitoring, and evaluating one's thinking during work tasks (Flavell, 1979). Moreover, when performing the task, they often need to select strategies and adapt to them, especially when tasks change. This is the main pathway explaining transfer beyond the immediate job (Zimmerman, 2002; OECD, 2019).

Self-Efficacy and Learning Agency

Another key concept is self-efficacy and agency, supported across all four theories of experiential, transformative, situational, and metacognitive learning theories. Self-efficacy of

adults to whether or not adults will persist, seek feedback, and engage in challenging tasks (Bandura, 1997), depend on two factors: (1) confidence, and (2) perceived control. Learning agency, on the other is a crucial factor that describes the likelihood of adults entering into the learning cycles and using metacognitive strategies (Billet, 2011; Raelin, 2008).

Skill Use and Deliberate Cognitive Practice

Skill use is the frequency and intensity of literacy/numeracy/problem-solving use at work. While deliberate cognitive practice helps strengthen fluency and builds cognitive routines, operating with or without deep reflection (Ericsson, Krampe, & Tesch-Römer, 1993). Both skill use and deliberate cognitive practice are conceptual elements from the experiential and situated learning theories from Kolb and Lave & Wenger, respectively (Kolb, 2015; Lave & Wenger, 1991).

Outcomes Layer from Adult Cognitive Development

In the study, ACD gains don't just imply "more skills", but reflect improved ability to adapt and transfer learning to new contexts. ACD is expressed as both an adult's specific knowledge, abilities, and techniques required to perform effectively within a particular field (domain skills), and the mind's ability to adjust thinking, learning, and decision-making in response to dynamic environments, goals, and/or challenges (adaptive cognition) (Illeris, 2011; OECD, 2019). In the PIAAC dataset, ACD is described as literacy, numeracy, and adaptive problem-solving in technology-rich environments (OECD, 2016). Together, they bring cognitive flexibility and transfer readiness in an adult, concepts that can be very well related to metacognitive (Flavell, 1979) and transformational learning theories (Mezirow, 1997, 2000).

Conditional Layer for Structural conditioning and exogenous covariates shaping the WBL Affordances

The control layer works as a context layer, comprising of the sector or occupation, and socio-economic status (SES) factors explaining background differences. Based on elements of situated learning theory (Billet, 2001; Lave & Wenger, 1991), the control layer provides structural conditions shaping the learning environment. They need to be adjusted even when the main interest is mechanisms (Rubenson & Desjardins, 2009; Tynjälä, 2013). Sector or occupation affects task structure (Felstead et al., 2016; Green & Gallie, 2020), learning culture, and technology exposure, whereas SES affects access to training, stability, time resources, and cumulative advantage (Desjardins, 2017; Heckman & Mosso, 2014; OECD, 2019).

Reciprocal Feedback Layer

The main idea of the reciprocal feedback layer within the conceptual framework is to see ACD as both an outcome and a resource (Desjardins, 2017; Heckman & Mosso, 2014) that enables higher -quality WBL, creating a feedback loop over time. As ACD increases, adults can handle more complex tasks, self-directed learning, and participate more centrally in communities of practice (Lave & Wenger, 1991; Wenger, 1998), increasing exposure to richer WBL affordances (Billet, 2011), reinforcing the cycle.

Dynamics of Symbiotic Relationship

The WBL-ACD symbiosis functions through a series of dynamic, mutually reinforcing loops that enable adults to learn, adapt, and transfer skills across various contexts (Raelin, 2008; Illeris, 2011). The dynamics can be broken down into three phases: (1) Initiation – In this phase, through workplace learning experiences (e.g., participation in authentic tasks), cognitive engagement is induced. WBL provides adults with opportunities to apply their core ACD dimensions (e.g., literacy, numeracy, and adaptive problem-solving skills) that help raise ACD growth through experiential learning (Kolb, 2015). The participation in authentic work aligns

with the situated learning principles, where participation in communities of practice facilitates knowledge construction (Lave & Wenger, 1991); (2) Reinforcement. As adults develop stronger cognitive capabilities, they become better able to analyze, reflect upon, and adapt to increasingly complex workplace challenges. In turn, these enhanced cognitive capacities support more effective engagement in workplace learning opportunities, creating a reciprocal relationship in which WBL and ACD mutually reinforce one another (Mezirow, 1991; Bandura, 1997). (3) Transfer. The benefits arising from the WBL-ACD nexus extend beyond the workplace as adults apply and transfer acquired knowledge and skills to diverse contexts, including everyday decision-making and civic participation (OECD, 2019). This broader application supports lifelong learning, adaptability, and resilience, positioning the WBL-ACD symbiosis as a foundation for sustainable skills development across work and life domains (Ioannidou & Desjardins, 2020).

Enablers and Inhibitors of the Symbiosis

Workplace sectors can act as both enablers and inhibitors of the WBL-ACD symbiotic relationship, depending upon the nature of the workplace environment and job features. The enabling factors include sectors that are cognitively demanding, letting adults be involved in decision-making, problem-solving, and leadership activities. These jobs stimulate and support neuroplasticity, resulting in better cognitive health over time (Stern, 2009; Skirbekk, & Edwin, 2024). Similarly, workplace sectors that provide opportunities for continuous learning and support flexibility enable improved ACD outcomes (Radovan, 2024; Shiri et al., 2023).

Table 2-1 Summarizes the Characteristics of Workplace Sectors, their Impact within the Symbiosis Framework, and Sector-Based Examples.

Workplace Sector Characteristics	WBL-ACD Impact	Examples of Sectors

High complexity, decision-making	Enabling	Business/Management, Education/Training, STEM
Physically hazardous	Inhibiting	Construction, Manufacturing
Shift work and stress	Inhibiting	Healthcare, Emergency services
Sedentary (but mentally active)	Mixed	Technical (office work, administrative)
Rigid roles (less challenging)	Inhibiting	Routine tasks

The inhibiting factors may range from work types involving physically demanding activities, such as construction, farming, and manufacturing, to sectors with high levels of stress, shift work, and sedentary activities. All these types of work sectors tend to impair cognitive functioning (Bufano et al., 2024; Khan et al., 2023; Zotcheva et al.,2023).

Therefore, sectoral patterns and context play a critical role in the symbiotic relationship between WBL-ACD. There is a detailed section on sectoral patterns to bring more context to the symbiotic WBL-ACD nexus.

Feedback Processes in the WBL-ACD Symbiosis Nexus

Several theoretically proposed feedback processes may help explain the reciprocal relationship between workplace-based learning (WBL) and adult cognitive development (ACD). First, experiential learning emphasizes the role of engagement in activities, reflection, and the application of knowledge in subsequent experiences (Kolb, 1984; Eraut, 2004). Second, metacognitive and self-regulatory processes involve planning, monitoring, and evaluating learning activities, potentially strengthening learning and adaptive performance (Zimmerman, 2002; Sitzmann & Ely, 2011). Third, learning transfer involves applying acquired knowledge and skills to workplace situations, with its effectiveness shaped by individual characteristics and organizational conditions (Baldwin & Ford, 1988; Bell & Kozlowski, 2008). Furthermore, workplace learning opportunities depend on both organizational affordances and individuals' engagement with those opportunities (Billett, 2001).

Collectively, these perspectives provide a theoretical rationale for potentially reciprocal associations between WBL and ACD, whereby workplace experiences may support cognitive proficiency while existing proficiency may facilitate engagement in further learning opportunities. However, the proposed feedback processes represent theoretical mechanisms rather than longitudinal relationships directly established by the present cross-sectional analysis.

Applications and Implications

The symbiotic WBL-ACD framework has critical applications and implications at individual, policy, and community levels. At an individual level, adults will utilize their ACD dimensions to seek and participate fully in WBL opportunities, and in turn, WBL will promote their ACD gains (Billett, 2014; Ioannidou & Desjardins, 2020; OECD, 2013). Thus, practice and program design for training programs must be capable of supporting the dynamic or reciprocal loop, and for this, adequate support and resources (e.g., inclusive, scaffolded, iterative design structure for WBLs) are much needed for efficacy.

Considering the potentially reciprocal associations between workplace-based learning (WBL) and adult cognitive development (ACD), the findings suggest two policy priorities for adult learning systems: (1) integrating WBL more systematically into broader adult learning infrastructures by connecting workplace experience, reflective practice, and collaborative learning (Raelin, 2008); and (2) promoting equitable access to workplace learning opportunities through organizational arrangements that support employee participation, guidance, reflection, and engagement in learning-rich work activities (Billett, 2001, 2014).

In communities, organizations can leverage symbiotic relationships by enhancing the engagement of adult learners in community-focused projects and focusing on building cognitive skills and social capital. This addresses local needs through problem-based learning (Annie E.

Casey Foundation, 2021). Overall, applying the WBL-ACD symbiotic nexus at all three levels ensures improved effectiveness of adult learning, equitable workforce development policies, and community empowerment (Ross et al., 2020).

Contextual Factors Shaping the WBL-ACD Symbiosis

Contextual factors tremendously impact the symbiotic relationship between WBL and ACD. At the workplace level, factors such as task design, organizational culture, and training opportunities influence the effectiveness of WBL in reinforcing ACD (Eraut, 2004; Radovan, 2024). At the individual level, baseline skills, motivation, and self-efficacy influence engagement and outcomes (Bandura, 1997). At the macro-policy level, the factors that matter the most include adult learning systems, recognition of workplace learning, and equity in access, which define the scope of opportunities (OECD, 2013; Ioannidou& Desjardins, 2020).

Finally, at the meso-level, sectoral context acts as a dominant factor. Industries like healthcare, STEM/Technical fields, and Education/Training are cognitively demanding, requiring rapidly evolving tasks that need continuous stimulation of ACD. Whereas industries such as culinary/Food-related and Management/business roles involving manufacturing often require manual learning that reinforces different ACD dimensions (Billett, 2014; OECD, 2019). Thus, sectoral variations shape the depth, frequency, and transferability of WBL, making them central to understanding how WBL catalyzes ongoing ACD growth.

Chapter Summary

This chapter discusses how strengthening the link between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) is recognized as essential for enhancing learning processes and improving adults' real-life decision-making. The limited integration of WBL into everyday decision-making underscores the need for theoretical clarity. This study introduces the WBL–

ACD symbiotic framework, grounded in established adult learning theories, including experiential, transformative, situated, and metacognitive perspectives (Kolb, 2015; Mezirow, 1997; Lave & Wenger, 1991; Flavell, 1979) to illustrate how WBL can foster cognitive and behavioral adaptation in workplace and life contexts.

A growing body of research demonstrates a reciprocal relationship between WBL and ACD, whereby engagement in WBL supports cognitive gains and increased cognitive capacity enhances WBL participation (Billett, 2014; Eraut, 2004). Metacognitive mechanisms such as practice, reflection, collaboration, and digital engagement facilitate this reciprocity, though socio-demographic, and motivational factors act as mediators (Gigerenzer & Gaissmaier, 2011). These complexities call for inclusive and adaptable WBL programs embedded in lifelong learning and equity frameworks, with attention to digital readiness and baseline skill variation (Baltes, 1997).

Despite emerging insights, the literature remains fragmented. Key gaps include inconsistent definitions of WBL, limited attention to broader ACD dimensions (e.g., metacognition, executive function), underexploration of reciprocal models, and insufficient analysis of sectoral practices and equity in WBL access. Future research should adopt longitudinal, dynamic, and equity-centered approaches to better understand how the WBL–ACD nexus shapes decision-making across diverse life contexts.

Chapter 3 - Methodology

Introduction

Adults in today's knowledge-based economy are expected to continually update their skills through workplace experiences rather than relying solely on formal education. However, the reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD), whereby workplace experiences enhance cognitive capabilities and stronger cognitive skills facilitate further engagement in workplace learning, remains insufficiently understood. Although previous research has typically examined these relationships in a single direction, limited evidence exists regarding their reciprocal nature. This study therefore examines the existence and nature of a mutually reinforcing WBL-ACD nexus and investigates how different workplace learning experiences are associated with adult cognitive development. Using a family of structural equation modeling (SEM) to estimate reciprocal relationships and SEM-informed static policy optimization to identify the workplace-learning actions associated with the highest expected cognitive outcomes across observed WBL-ACD states, the study provides an evidence-based framework for understanding and optimizing workplace learning among employed adults.

This chapter begins by briefly discussing the research questions and research hypotheses. It then outlines the quantitative research design, conceptual alignment, and the data analysis methods chosen for the study. In doing so, it describes the data source, sample, and variables, including the operationalization of WBL indicators, APS measures, and socio-demographic

covariates. Finally, the chapter concludes by discussing the ethical considerations and limitations of the study.

Research Questions and Hypotheses

The study revolves around two main research questions and two hypotheses described below:

RQ1: What is the nature of the reciprocal association between Work-Based Learning (WBL) and the three dimensions of Adult Cognitive Development (ACD)?

H_{01}: There is no statistically significant reciprocal relationship between adults' engagement in WBL and their ACD levels, measured through literacy, numeracy, and adaptive problem-solving (APS) proficiency.

H_{11}: There is a statistically significant reciprocal relationship between adults' engagement in WBL and their ACD levels, such that participation in WBL enhances cognitive proficiency, while stronger cognitive foundations further promote engagement in WBL activities.

RQ2: How are different types and intensities of WBL experiences associated with adults' cognitive development outcomes in literacy, numeracy, and adaptive problem-solving (APS)?

H_{02}: Differences in the types and intensities of WBL experiences are not significantly associated with adults' literacy, numeracy, and APS outcomes.

H_{12}: Different types and intensities of WBL experiences are significantly associated with adults' literacy, numeracy, and APS outcomes, with the relative value of workplace-learning strategies varying across WBL-ACD states and cognitive domains.

Research Design

This research employs a cross-sectional, simulation-augmented quantitative modeling design (Figure 3.1), integrating structural equation modeling (SEM), assessment-informed static optimization, and bootstrap-based stability assessment. The framework examines competing

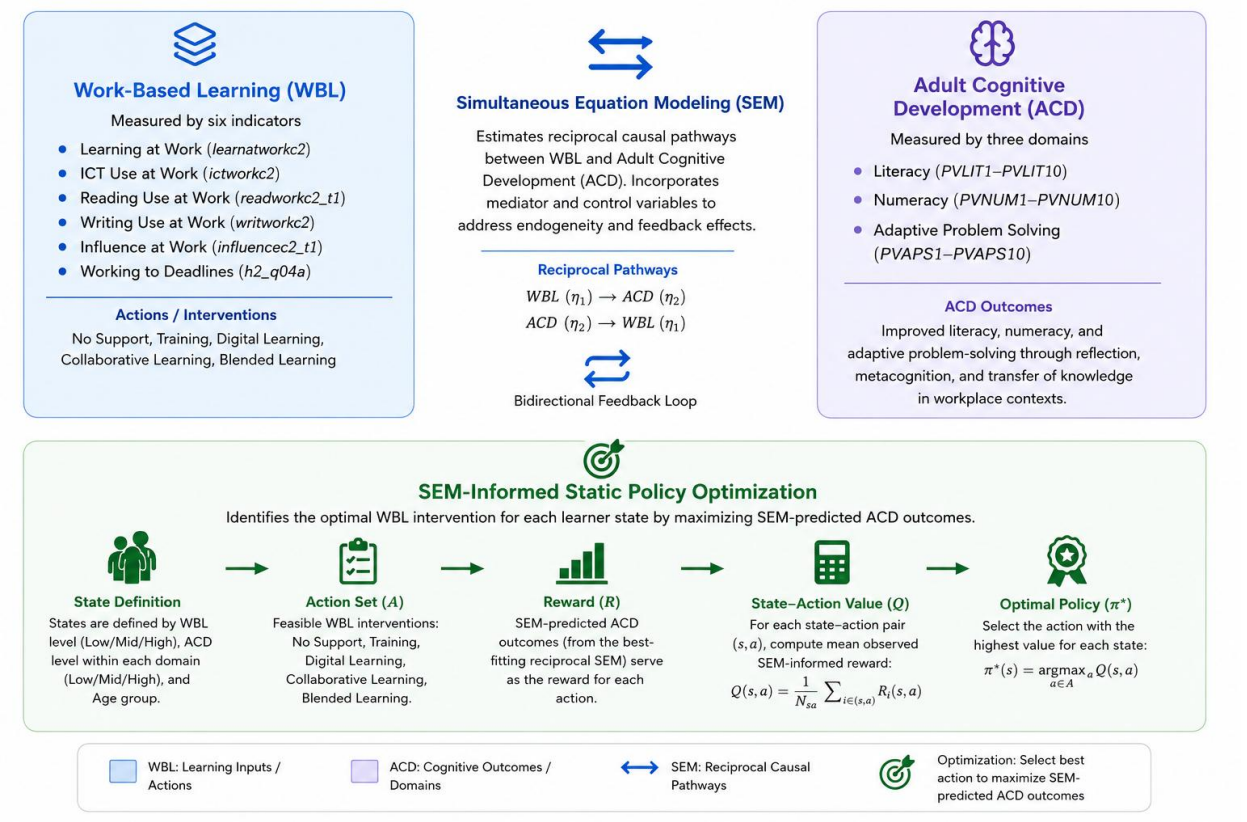
directional and reciprocal associations between workplace-based learning (WBL) and adult cognitive development (ACD) and evaluates alternative workplace learning strategies using SEM-informed expected outcomes. Bootstrap resampling is used to assess the stability of the resulting strategy rankings. To address the reciprocal nature of the symbiotic Work-Based Learning (WBL) and Adult Cognitive Development (ACD) nexus, the study combines structural estimation through a family of Structural Equation Modeling (SEM), including simultaneous equation modeling (Bollen, 1989), with SEM-informed static policy optimization. Specifically, competing SEM specifications are used to characterize the structural associations between WBL and ACD, including potential reciprocal relationships, while empirical state-action reward estimates informed by the SEM are used to identify the highest-reward workplace-learning strategy for each observed WBL-ACD state.

To translate SEM estimates into state-specific workplace-learning recommendations, this study employs an SEM-informed offline static policy optimization framework. The optimization is performed offline using the observed PIAAC dataset and does not involve sequential interactions, reinforcement learning, or dynamic state transitions. Instead, the framework defines empirical WBL-ACD states, estimates survey-weighted state-action rewards informed by the fitted SEM, and identifies the workplace-learning action associated with the highest estimated reward within each state.

Unlike reinforcement learning approaches that rely on sequential interactions and dynamic state transitions, the proposed framework derives optimal intervention policies directly from observed data, providing interpretable and evidence-based recommendations. This integrated approach aligns with experiential and reflective learning theories (Raelin, 2008; Tynjälä, 2008), conceptualizing adult learning as a reciprocal and adaptive process in which

work experiences and cognitive development mutually reinforce one another over time (Billett, 2011).

Figure 3-1 The integrated quasi-experimental design captures the bidirectional WBL–ACD nexus via SEM and validates it through SEM-informed static policy optimization, illustrating a self-optimizing system where experience strengthens cognition and cognition enriches experience.



SEM captures the reciprocal structural relationships between Work-Based Learning (WBL) and Adult Cognitive Development (ACD), while accounting for relevant mediating and exogenous factors. The SEM-informed static policy optimization framework then extends these causal estimates into a decision-support model by evaluating the observed effectiveness of alternative WBL interventions across empirical WBL-ACD states. Rather than relying on

sequential learning or reinforcement learning algorithms, the framework uses state-specific empirical reward estimates to identify the work-based learning strategy associated with the highest expected cognitive outcomes. Integrating SEM with static policy optimization therefore moves the study beyond estimating reciprocal relationships alone by translating causal evidence into actionable, data-driven recommendations. This approach enables the identification of optimal WBL interventions for individuals occupying different empirical learning states while maintaining transparency, interpretability, and consistency with the underlying structural model.

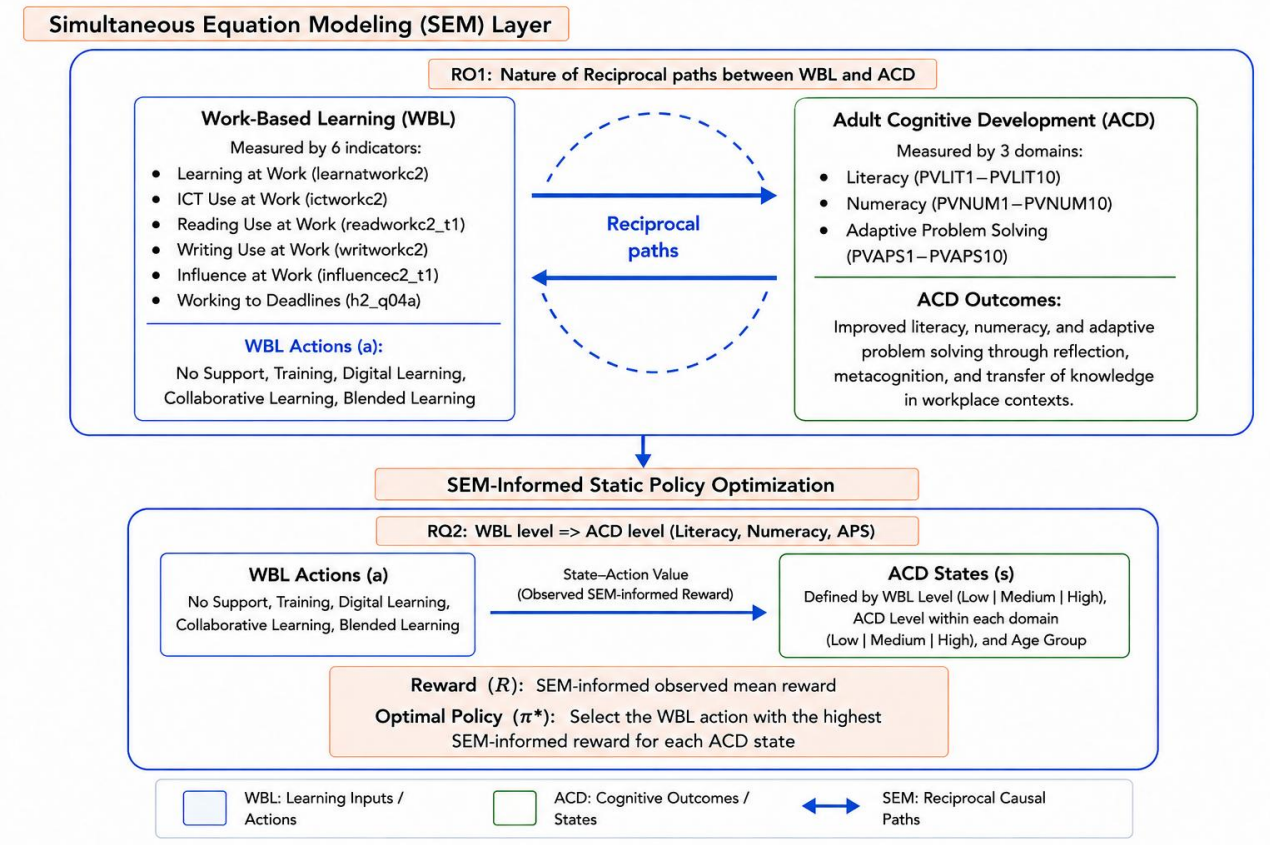
The SEM-informed static policy optimization framework proposed in this study builds on established principles of structural equation modeling (Bollen, 1989; Kline, 2023) and evidence-based policy optimization (Murphy, 2003; Zhao et al., 2012), while introducing a novel integration specifically designed for cross-sectional work-based learning data.

Figure 3.2 illustrates the alignment between the research questions and the proposed analytical framework. The research design directly corresponds to the objectives of the two research questions. The first research question (RQ1), which examines the nature of the reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD), is addressed using Simultaneous Equation Modeling (SEM). SEM estimates the bidirectional structural pathways between WBL and ACD while accounting for the specified mediating and exogenous variables, thereby evaluating the reciprocal associations between the two constructs.

The second research question (RQ2), which examines how different levels and forms of WBL relate to ACD outcomes, is addressed through SEM-informed static policy optimization. Building on the best-fitting SEM, individuals are classified into empirical WBL-ACD states, and state-specific rewards are estimated from the SEM-predicted cognitive outcomes. The

optimization framework then identifies the WBL action associated with the highest expected cognitive reward for each empirical state. This approach extends associational estimation into evidence-based decision support by translating reciprocal structural relationships into optimal, state-specific work-based learning recommendations. Together, the SEM and static policy optimization layers provide both an explanation of the reciprocal WBL-ACD nexus (RQ1) and a framework for identifying the most effective WBL strategies across different learner states (RQ2).

Figure 3-2 Alignment between Research Question and Research Design.



Conceptual Alignment

The methodological framework of this study is deeply rooted in established theories of adult learning, cognition, and workplace learning. The integration of Simultaneous Equation

Modeling (SEM) and SEM-informed static policy optimization reflects not only a methodological innovation but also a synthesis of experiential, transformative, situated, and metacognitive learning principles. Together, these theoretical perspectives explain how adults acquire knowledge through workplace experiences, regulate and apply cognitive processes, and respond to varying learning opportunities within occupational contexts. Consistent with these perspectives, SEM captures the reciprocal relationships between Work-Based Learning (WBL) and Adult Cognitive Development (ACD), while the static policy optimization framework translates these relationships into evidence-based, state-specific recommendations for work-based learning interventions.

Table 3.1 illustrates how each adult learning theory contributes distinct yet complementary perspectives to the Symbiotic WBL-ACD framework. Collectively, these theories explain how adults acquire knowledge through workplace experiences, reflect on and regulate their cognitive processes, and apply learning within authentic work environments (Billett, 2011; Raelin, 2008). Kolb's Experiential Learning Theory provides the conceptual foundation for understanding how workplace experiences facilitate cognitive development through cycles of experience, reflection, conceptualization, and experimentation (Kolb, 1984). Mezirow's Transformative Learning Theory emphasizes critical reflection and perspective transformation as mechanisms through which work experiences reshape adult cognition (Mezirow, 1997). Lave and Wenger's Situated Learning Theory positions learning within authentic workplace contexts and communities of practice, highlighting the importance of social participation in cognitive development (Lave & Wenger, 1991). Flavell's Metacognitive Theory explains how self-regulation, monitoring, and reflective thinking support continuous cognitive growth (Flavell, 1979). Together, these theoretical perspectives provide the conceptual

foundation for the reciprocal relationships estimated through Simultaneous Equation Modeling (SEM) (Bollen, 1989). The SEM-informed static policy optimization framework extends these theoretical insights by translating the estimated structural relationships into evidence-based, state-specific recommendations regarding the work-based learning strategies associated with the highest expected cognitive outcomes.

Table 3-1 The Integration of Adult Learning Theories with SEM -Informed Static Policy Optimization Analysis.

Learning Theory	Core Mechanism / Construct	Representation in SEM (Structural Modeling)	Representation in SEM-Informed Static Policy Optimization	Analytical / Interpretive Role
Kolb's Experiential Learning (1984)	Learning through iterative experience, reflection, conceptualization, and experimentation	WBL latent construct, constructed through workplace learning experiences, predicts ACD domains.	Alternative WBL actions represent different forms of workplace learning whose expected outcomes are compared across empirical learner states.	Explains how workplace experiences contribute to cognitive development and informs the evaluation of alternative learning strategies.
Mezirow's Transformative Learning (1997)	Critical reflection and reframing of assumptions	Reciprocal pathways between WBL and ACD capture how reflective workplace experiences contribute to cognitive development.	Policy optimization identifies WBL strategies associated with the greatest expected cognitive gains for learners occupying different empirical states.	Explains how reflective workplace learning contributes to changes in adult cognition and supports evidence-based intervention selection.
Lave & Wenger's Situated Learning (1991)	Learning through participation in authentic communities of practice	Collaborative and workplace-based learning indicators represent authentic learning environments within the WBL construct.	State-specific recommendations recognize that optimal workplace learning strategies may differ across empirical WBL-ACD profiles.	Highlights the importance of authentic workplace contexts in shaping learning opportunities

Learning Theory	Core Mechanism / Construct	Representation in SEM (Structural Modeling)	Representation in SEM-Informed Static Policy Optimization	Analytical / Interpretive Role
				and cognitive development.
Flavell's Metacognitive Theory (1979)	Self-regulation, monitoring, and control of cognitive processes	Reciprocal relationships between WBL and ACD reflect the role of self-regulated cognition in workplace learning.	Different empirical learner states reflect variation in cognitive readiness, informing state-specific policy recommendations.	Explains how metacognitive regulation supports adult learning and cognitive growth across different workplace learning contexts.
SEM-Informed Static Policy Optimization (Bollen, 1989)	Evidence-based optimization of workplace learning interventions (exploratory)	SEM estimates reciprocal structural relationships between WBL and ACD (Bollen, 1989).	State-specific expected rewards are compared to identify the WBL action associated with the highest expected cognitive outcome.	Translates reciprocal structural relationships into interpretable, evidence-based recommendations for workplace learning interventions.

Methodological Positioning and Original Contribution

Previous quantitative research has established important relationships between workplace experiences, adult learning, and cognitive proficiency. Lopes et al. (2020) examined the associations between the social characteristics of work and adult cognitive skills using U.S. PIAAC data, while Scandurra and Calero (2019) employed structural equation modeling to investigate how adult skills are configured in relation to educational and contextual factors. Gauly and Lechner (2019) further examined the directionality of the relationship between job-related training and adult literacy using longitudinal PIAAC data, highlighting the importance of

distinguishing whether workplace learning contributes to cognitive proficiency or whether existing proficiency influences participation in learning opportunities.

Building on this literature, the present dissertation study contributes an integrated analytical framework that combines two complementary components. First, it systematically compares competing forward, reverse, reciprocal, and correlated-disturbance structural equation specifications to examine the consistency of associations between workplace-based learning (WBL) and adult cognitive development (ACD) across literacy, numeracy, and adaptive problem solving using U.S. PIAAC 2023 data.

Second, it extends the analysis from examining associations to assessment-informed decision support by integrating SEM-derived expected outcomes with a cross-sectional static optimization framework. This approach compares alternative workplace learning strategies across nine WBL–ACD states within each cognitive domain and employs bootstrap resampling to assess the stability of the resulting strategy rankings. The study's methodological contribution therefore lies in combining competing structural model assessment with transparent, uncertainty-informed static decision optimization within a unified adult learning framework. Given the cross-sectional research design, the resulting associations and strategy rankings are interpreted as model-dependent evidence rather than identified causal effects or dynamically optimized intervention policies.

Data Collection and Variables

Dataset Collection

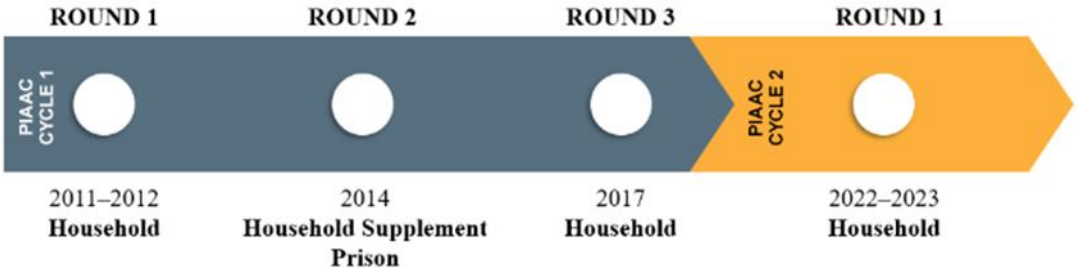
The primary data used is the most extensive global dataset on adult skills and competencies, the Program for the International Assessment of Adult Competencies (PIAAC) 2023. The PIAAC 2023 Public Use File (PUF) typically does not require Institutional Review

Board (IRB) approval because the dataset is fully de-identified and publicly available. However, as an additional step, final institutional IRB approval was requested and approved.

The PIAAC dataset initiative for the United States started in 2008. The first data collection phase occurred in two rounds of cycle one between 2011 - 2017: (a) Round 1-conducted between August 2011 and April 2012 with a nationally representative sample of 5000 adults aged 16-65 (US PIAAC Gateway, assessed on 08/07/2025), and (b) Round 2-conducted in 2013-2014, oversampling young adults (16-34), unemployed individuals (16-65), and including older adults (66-67). The number of participants added was 3,660, and thus the total number of participants was 8,700 adults (US PIAAC Gateway, assessed on August 7, 2025).

The main data collection for the US PIAAC Cycle 2 survey was conducted between August 2022 and June 2023, involving approximately 4,600 adult individuals aged 16–74. The survey assessed literacy, numeracy, and a new adaptive problem-solving dimension, with background data collected through computer-assisted interviews and cognitive assessments on a tablet platform. The new aspects of this survey were (1) the socio-emotional skills module and (2) the financial literacy questions. All the instruments used were internationally standardized and implemented in the US under the supervision of the NCES, with the assistance of the OECD. The survey is a unique warehouse of high-quality nationally representative data for examining ACD, WBL, and socio-demographic factors in a dynamic economy. Figure 3.3 describes the timing and schedule of Cycle 2 of the PIAAC survey.

Figure 3-3 Timing and Schedule of Cycle 2 of the PIAAC survey 2023 in the US.



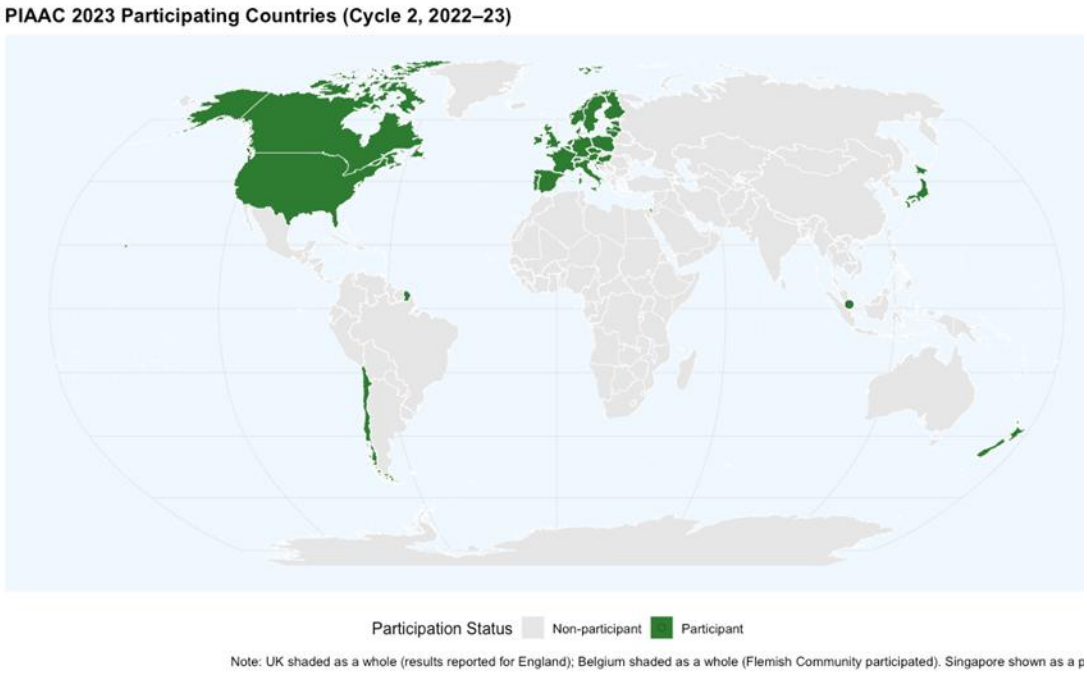
This survey employs a multistage sampling procedure, selecting a representative sample of adults aged 16-74 from national registries or census data (the sampling frame). The detailed process of sampling involves data stratification, where the population is first divided into strata based on selected relevant characteristics, such as geographic regions. Once the strata are determined, clusters, such as geographic areas, are selected using probability sampling methods within each stratum. Lastly, the individuals within the selected clusters are chosen using probability sampling methods. The rigorous quality checks of the PIAAC consortium ensure the quality of the data. The sample size varies by country; however, it is sufficiently large to produce reliable estimates for adult skills and competencies.

The PIAAC data is generated from the survey on adults' skills. It is a computer-based household international survey of adults aged between 16 and 74. It takes place once every ten years. This survey aims to assess adults' key information-processing skills in literacy, numeracy, and problem-solving in technology-rich environments, which are essential for individuals to participate in societal actions and for economies to thrive. This also includes information and data on how adults use their skills and competencies at home (OECD, accessed September 28, 2024).

The participating countries in PIAAC Cycle 2 (2022-23) include: Austria; Belgium (Flemish region); Canada; Chile; Croatia; Czechia; Denmark; Estonia; Finland; France; Germany; Hungary; Ireland; Israel; Italy; Japan; Korea (South Korea); Latvia; Lithuania;

Netherlands; New Zealand; Norway; Poland; Portugal; Singapore; Slovak Republic; Spain; Sweden; Switzerland; United Kingdom (England); United States (See Figure 3.4; Map generated using R code in the study).

Figure 3-4 World Map showing participating countries in Cycle 2 of the PIAAC survey 2023.



Variables and Measures

This study investigates the nature of the reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) using an integrated SEM Informed Static Optimization Framework. Accordingly, variables were selected based on both theoretical relevance and empirical availability within the 2023 Programme for the International Assessment of Adult Competencies (PIAAC). The variables represent three major components of the proposed Symbiotic WBL–ACD Nexus: (a) the workplace learning environment and learning experiences, (b) adult cognitive development, and (c) the individual and contextual characteristics that shape this reciprocal relationship. Variables were subsequently incorporated

into either the structural equation models or the static policy optimization analyses according to their analytical function.

Unlike conventional recursive structural equation models that distinguish fixed exogenous predictors from endogenous outcomes, the present study specifies a non-recursive (simultaneous) structural equation model in which Work-Based Learning (WBL) and Adult Cognitive Development (ACD) are jointly endogenous constructs. Each construct functions as both an explanatory variable and an outcome variable within separate structural equations, reflecting the reciprocal nature of the proposed Symbiotic WBL–ACD Nexus. In non-recursive SEM, endogenous variables may simultaneously influence one another, provided that the model is theoretically justified and satisfies appropriate identification conditions (Bollen, 1989; Hayduk, 1987). Consequently, the distinction between predictor and outcome is not fixed but depends on the structural equation being estimated (Kline, 2023). Therefore, the variables in this study are organized according to their conceptual and analytical roles rather than a fixed predictor–outcome classification.

Endogenous Variable Work-Based Learning (WBL)

Work-Based Learning (WBL) served as one of the two primary endogenous constructs in the reciprocal structural equation models. Consistent with workplace learning theory, WBL was conceptualized as a multidimensional construct representing adults' engagement in authentic workplace learning opportunities through everyday work activities rather than participation in a single training program. This conceptualization recognizes that workplace learning develops through participation in meaningful work tasks, interaction with colleagues, problem-solving, technology use, and opportunities for reflection (Billett, 2001; Raelin, 2008).

The latent WBL construct was operationalized using six workplace indicators available in the PIAAC 2023 background questionnaire (Table 3-2). These are standardized workplace learning indices developed by the OECD and one ordinal frequency variable. These indicators collectively capture different dimensions of workplace learning, including learning engagement, workplace literacy demands, digital skill use, communication demands, and cognitive task complexity.

Table 3-2 Indicators used to operationalize the Work-Based Learning Construct.

Variable / Construct	PIAAC Variable(s)	Measurement Level	Description
Learning at work	learnatworkc2	Continuous index (Standardized OECD index)	Index of learning during work
ICT use at work	ictworkc2		Index of ICT skill use at work
Reading use at work	readworkc2_t1		Reading-related workplace tasks
Writing at work	writworkc2		Writing-related workplace tasks
Influencing skills	influencec2_t1		Communication and influencing tasks
Working to deadlines	h2_q04a	Ordinal	Frequency of high-speed or deadline-driven work

As discussed in Chapter 2, Work-Based Learning (WBL) is conceptualized as a multidimensional construct encompassing experiential, reflective, collaborative, knowledge integration, skill development, contextual, and lifelong learning dimensions (Billett, 2001; Raelin, 2008). These dimensions provide the theoretical foundation for the study. However, the PIAAC 2023 dataset does not include direct measures corresponding to each theoretical dimension. Therefore, for the empirical analyses, WBL was operationalized as a single latent construct measured by six workplace indicators that collectively reflect adults' engagement in workplace learning activities, cognitive demands, and skill use. This operationalization aligns with the OECD's measurement framework, which represents workplace learning through

observed workplace behaviors and learning opportunities rather than through separate theoretical dimensions (OECD, 2024).

Finally, these indicators were standardized and modeled as a latent construct within the simultaneous equation models. Internal consistency and construct validity were subsequently evaluated using Cronbach's alpha, McDonald's omega, and confirmatory factor analysis before structural model estimation.

Endogenous Variable Adult Cognitive Development (ACD)

Adult Cognitive Development (ACD) constituted the second endogenous construct in the reciprocal structural equation model. ACD was represented by three cognitive domains assessed in PIAAC: literacy proficiency, numeracy proficiency, and adaptive problem-solving (APS). Literacy represents adults' ability to understand, evaluate, and use written information. Numeracy reflects the ability to interpret and apply mathematical information in everyday situations. Adaptive problem-solving represents the ability to solve unfamiliar and dynamic problems through reasoning, planning, monitoring, and adaptation.

PIAAC reports ten plausible values for each cognitive domain to account for measurement uncertainty. Rather than combining these domains into a single composite cognitive index, literacy, numeracy, and APS were analyzed separately throughout the reciprocal SEM analyses to preserve domain-specific interpretation and examine whether reciprocal WBL–ACD relationships differed across cognitive competencies.

Table 3-3 summarizes the ACD measures, PIAAC variable code, measurement level, and their respective brief description.

Table 3-4 Adult Cognitive Development Measures.

Variable / Construct	PIAAC Variable(s)	Measurement Level	Description
Literacy	lit_pv1–pv10	Continuous (0–500)	Plausible values for literacy proficiency
Numeracy	num_pv1–pv10	Continuous (0–500)	Plausible values for numeracy proficiency
Adaptive Problem Solving (APS)	aps_pv1–pv10	Continuous (0–500)	Plausible values for adaptive problem solving

Plausible values (PVs) are used in the SEM-Q-Learning analysis. PVs are multiple-imputed estimates of an adult's ability (such as literacy, numeracy, or adaptive problem-solving) based on their test responses and background characteristics (e.g., education, occupation).

Each adult receives a set of ten PVs. Since PIAAC uses matrix sampling, not every adult gets the same test items. Each respondent answers just a subset of the complete set of items. Therefore, only a probability distribution of possible proficiencies is obtained, thereby discarding the possibility of estimating a precise ability score for each adult.

PIAAC applies several strategies to enable unbiased population-level estimates, which include:

1. Building a latent trait model (Item Response Theory, IRT),
2. Using background regressors (via a latent regression model), and
3. Drawing several random plausible values from each respondent's posterior ability distribution.

Each PV is not a separate test score; however, it is one random draw from the ability distribution. All ten PV scores are used, and results are appropriately combined following methodological procedures. In the present study, conceptually, these ten PVs are treated as ten imputed datasets. Therefore, in the SEM-Q-Learning framework, SEMs were estimated separately for each of the ten plausible values (Asparouhov & Muthén, 2010; Rutkowski et

al., 2014), and path estimates were combined according to Rubin's (1987) multiple-imputation rules. The resulting standardized path coefficients (γ, β) and latent cognitive estimates were subsequently used to parameterize adaptive reward structures within a Q-learning simulation of work-based learning (Baker & Siemens, 2014). This is both theoretically and computationally sound and efficient (Asparouhov & Muthén, 2010; Li et al., 2025; Muthén et. al., 2009; 2001; Ng et.al., 1999; Paxton et.al.; Rutkowski, 2014).

Mediating Variable

The mediating variables explain the mechanism of the pathway through which WBL produces changes in the ACD dimensions and vice versa. To investigate the mechanisms through which workplace learning contributes to cognitive development, the study included involvement in improving work organization or work processes as the mediating variable. This variable reflects employees' opportunities to actively participate in workplace improvement activities and organizational innovation rather than performing routine work alone.

Conceptually, participation in organizational improvement represents reflective engagement and active problem-solving, both of which have been identified as mechanisms through which workplace learning promotes adult cognitive development. Within the SEM framework, this variable was examined as a potential mediator linking WBL to ACD (Table 3-5).

Table 3-5 Mediating Variable for the SEM Analysis.

Variable / Construct	**PIAAC Variable(s)**	**Measurement Level**	**Description**
Organizational improvement	H2_Q14A	Ordinal	Involvement in improving work organization or work processes

Exogenous Control Variables

Several demographic and human capital characteristics were included as exogenous control variables to account for individual differences that may influence both Work-Based Learning (WBL) and Adult Cognitive Development (ACD). In the context of the simultaneous equation model, these variables are considered exogenous because they are assumed to originate outside the reciprocal WBL–ACD system and are not influenced by either endogenous construct within the model (Bollen, 1989; Kline, 2023). Instead, they serve as background characteristics that help isolate the reciprocal relationship between WBL and ACD by reducing potential confounding.

Previous research has consistently shown that age, gender, educational attainment, immigrant status, and self-rated health are associated with workplace learning opportunities, skill utilization, and adult cognitive proficiency (OECD, 2024). Accordingly, these variables were included to improve the precision of the estimated structural relationships while controlling for systematic differences among individuals. Table 3-6 summarizes the exogenous control variables, PIAAC variable code, measurement level, and their respective description.

Table 3-6 Exogenous Control Variables for the SEM-Informed Static Policy Optimization Analysis.

Variable / Construct	PIAAC Variable(s)	Measurement Level	Description
Age	AGEG10LFS	Ordinal categorical	Age grouped into ordered categories
Gender	GENDER_R	Binary	Male/Female
Educational attainment	EDCAT6_TC1	Ordinal categorical	Six-level educational attainment
Immigration status	IMGENC2	Binary	Immigrant status
Non-formal training	NFEEVER	Binary	Ever participated in non-formal education or training (Yes/No)
Self-rated health	I2_Q03	Ordinal	Self-rated health

Workplace Learning Experiences: The Occupational Context

Although WBL was modeled as a latent construct within the SEM, the reinforcement learning analyses required WBL to be operationalized as alternative workplace learning experiences that adults could encounter during their careers.

Based on workplace learning theory and variables available within PIAAC, five learning experiences were evaluated (Table 3-7).

Table 3-7 Work-Based Learning experiences (policy optimization actions).

Learning Experience	Description
Employer-provided training	Formal workplace training opportunities
Digital learning	Learning through technology and digital work activities
Collaborative learning	Learning through teamwork and interaction
Blended learning	Combined workplace and structured learning
No additional learning support	Routine workplace participation without additional learning interventions

Within the SEM-informed static policy optimization framework, these workplace learning experiences represented alternative actions available within each observed WBL-ACD state. Expected cognitive outcomes were compared across the available workplace-learning actions, and the optimal policy was defined as the action associated with the highest expected cognitive outcome in each state.

WBL-ACD State Representation

To identify adaptive workplace learning strategies, reinforcement learning required the definition of discrete learning states. Both WBL and ACD were categorized into three developmental levels representing low, mid, and high levels of workplace learning engagement and cognitive proficiency, respectively.

Combining these levels generated a series of joint WBL–ACD states that represented the learner's current developmental condition. These states served as the environment within which

the reinforcement learning algorithm identified the workplace learning experience that maximized expected long-term cognitive gains.

Table 3-8 WBL-ACD State Representation.

WBL Level	ACD Level	Description
Low	Low	Limited learning engagement and cognitive proficiency
Low	Mid	Emerging cognitive development with limited WBL
Low	High	Strong cognition but limited workplace learning
Mid	Low	Moderate WBL with lower cognitive proficiency
Mid	Mid	Balanced developmental state
Mid	High	Strong cognitive foundation with moderate WBL
High	Low	High workplace learning but developing cognition
High	Mid	Strong workplace learning with growing cognition
High	High	Advanced workplace learning and cognitive proficiency

These state representations enabled the static policy optimization algorithm to estimate adaptive workplace learning policies that differed according to individuals' current developmental conditions rather than assuming a single optimal learning strategy for all adults.

To facilitate SEM-informed static policy optimization, continuous measures of Work-Based Learning (WBL) and Adult Cognitive Development (ACD) were transformed into a finite set of decision states. This state representation enables comparison of alternative workplace learning experiences across comparable levels of workplace learning engagement and cognitive proficiency while maintaining consistency with the cross-sectional nature of the PIAAC data. For each cognitive domain (literacy, numeracy, and adaptive problem solving), respondents' standardized WBL scores and domain-specific ACD scores were independently partitioned into three approximately equal-sized groups using empirical tertiles. Tertile thresholds were determined from the sample distribution using the 33.3rd and 66.7th percentiles. Respondents

with scores below the first threshold were classified as Low, those between the first and second thresholds as Mid, and those above the second threshold as High.

Formally, for a continuous variable X, the tertile classification was defined as:

$$S(X) = \begin{cases} \boldsymbol{Low}, \boldsymbol{X \leq Q_{0.333}} \\ \boldsymbol{Mid}, \boldsymbol{Q_{0.333} < X \leq Q_{0.667}} \\ \boldsymbol{High}, \boldsymbol{X > Q_{0.667}} \end{cases} \quad \text{.....Equation 3-1}$$

Where $Q_{0.333}$ and $Q_{0.667}$ denote the sample 33.3rd and 66.7th percentile values, respectively. The WBL tertile was then cross classified with the corresponding ACD tertile to create a two-dimensional state space. Combining the three WBL categories (Low, Mid, High) with the three ACD categories (Low, Mid, High) yielded nine distinct WBL–ACD states for each cognitive domain:

Table 3-9 Construction of the WBL–ACD State Space

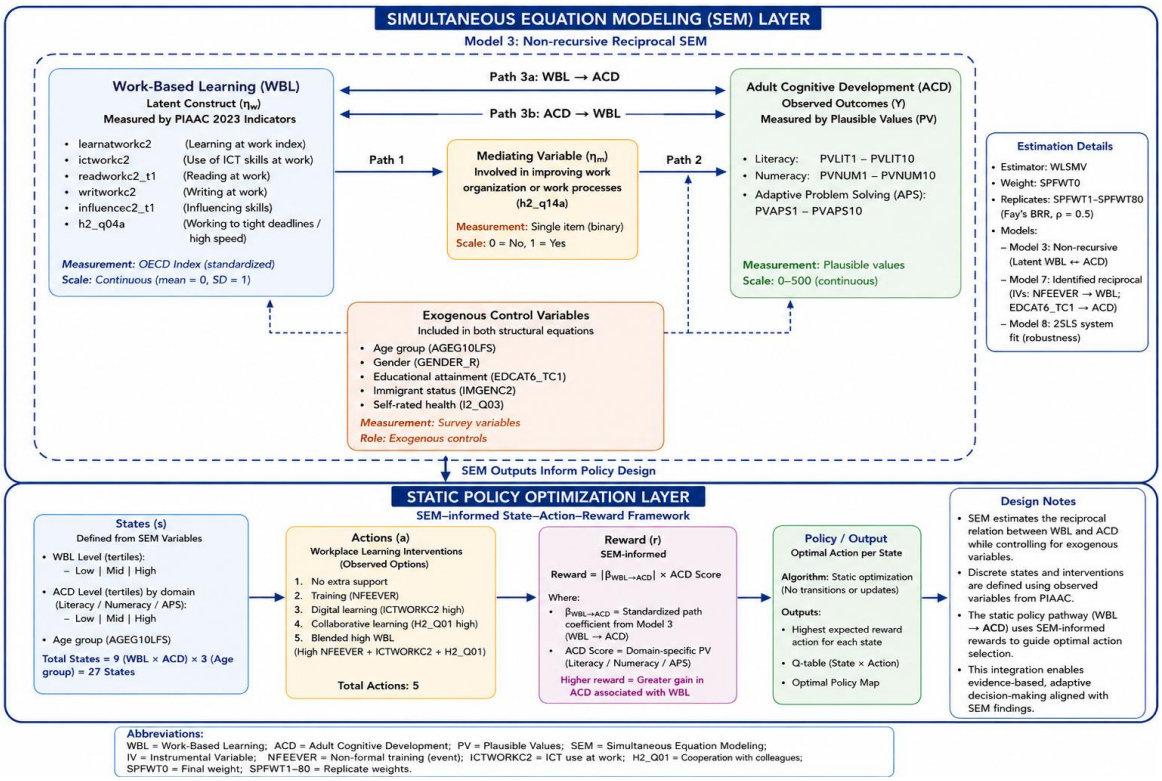
WBL Level	ACD Level	State
Low	Low	Low-Low
Low	Mid	Low-Mid
Low	High	Low-High
Mid	Low	Mid-Low
Mid	Mid	Mid-Mid
Mid	High	Mid-High
High	Low	High-Low
High	Mid	High-Mid
High	High	High-High

Because the optimization procedure was conducted separately for literacy, numeracy, and adaptive problem solving, the analysis comprised **27 domain-specific decision states** (9 states × 3 cognitive domains). The state boundaries were derived directly from the empirical distribution of the observed sample rather than from externally defined proficiency cut-points, ensuring balanced representation of respondents across the decision space and stable estimation of state-specific rewards.

The WBL-ACD states were not estimated by the simultaneous equation models. Rather, they were created during data preparation by classifying the standardized WBL index and the observed domain-specific ACD scores into tertiles. These tertile combinations defined the state space for the SEM-informed static policy optimization. The reciprocal SEM was subsequently used to estimate the structural relationship between WBL and ACD, and the standardized WBL → ACD coefficient from the preferred model (Model 1) was used to weight the observed rewards associated with each state-action combination. Thus, the SEM informed the reward function, while the tertile-based states provided the decision framework for identifying the workplace-learning action associated with the highest expected cognitive outcome.

Tertile partitioning was selected because it produces three interpretable levels of workplace learning and cognitive development while maintaining approximately equal numbers of observations in each category. Compared with arbitrary cut-points, empirical tertiles reduce sparse state problems, improve the stability of state-specific reward estimation, and provide a parsimonious state representation suitable for cross-sectional policy optimization.
Overall, the variables and the measurements are ensured to fit well within the scope of the SEM-Informed Static Policy Optimization analysis.

Figure 3-5 Illustrates Labeled Pathways that Depict Direct, Indirect, Mediating, and Feedback Relationships



In Figure 3-5, arrow 1 between WBL predictors and mediators indicates that variables such as learning at work, use of ICT skills at work, reading at work, writing at work, influencing skills, and working tight deadlines predict changes in the mediators (e.g., improving work organization). The arrow 2 between mediators and ACD outcomes indicates mediators directly predict ACD outcomes (literacy, numeracy, and adaptive problem solving). The possible mediation effects that may occur here are: (1) pure mediation, where the entire effect of the predictor on the outcome flows through the mediators, with no direct pathway from WBL predictors to ACD outcomes. What it means is that (1) WBL does not directly influence ACD outcomes, (2) WBL affects ACD only because it increases reflection, metacognition, skill use, and self-efficacy, and (3) once mediators are included, the direct effect disappears, or (2) partial mediation, where WBL affects ACD through mediators, and WBL also has a direct effect on

ACD. The partial mediation assumption assumes some portion of WBL's impact on ACD is due to improved reflection, metacognition, etc.; however, there is another portion of WBL's impact that is not explained by mediators, such as direct skill practice, job complexity, and exposure to cognitively demanding tasks.

Thus, the model estimates both mediated pathways (WBL → Mediators → ACD) and a direct pathway from WBL predictors to ACD outcomes. The presence and magnitude of the direct pathway are empirically evaluated, allowing for tests of both full and partial mediation.

Hence, in the Figure, there are 2 possible Arrow 3 placements: (1) is a dotted line modifying the mediators and the ACD path, not a direct causal arrow, meaning that moderators change the strength of the mediation pathway, not the mediators themselves, and (2) is a dotted line showing a direct path between WBL predictors and ACD outcomes.

Finally, arrow 4 (Double-headed arrow) shows a reciprocal or covariance relationship that controls variables and the moderator variables covariate but do not cause each other. In this study, it is assumed that sector/occupation and socio-economic status correlate with ICT skills, gender, education, or age, but no causal direction is assumed.

Instrumentation and Construct Validation

WBL and Mediator Indices

The Work-Based Learning (WBL) indices are developed during the present study as composite measures representing key experiential, reflective, and collaborative dimensions of workplace learning. Individual item scores from PIAAC and supplementary survey modules capturing training participation, skill use, and reflective practice were standardized and aggregated using factor loadings derived from exploratory factor analysis (EFA). Items with loadings ≥ 0.40 were retained to ensure conceptual and statistical coherence. Confirmatory factor analysis (CFA)

subsequently validated the three-dimensional WBL model, confirming strong inter-item relationships and theoretical alignment with experiential and situated learning principles. Higher composite scores indicated stronger engagement in WBL processes.

Reliability Tests and Construct Validity

The reliability and validity of the WBL indices was examined using Cronbach's α and McDonald's ω, with an acceptable range of internal consistency across items. In education research, reliability coefficients of 0.70 or higher are generally considered acceptable, with values exceeding 0.80 indicating good internal consistency (Nunnally & Bernstein, 1994; Kline, 2016). Confirmatory Factor Analysis (CFA) results demonstrated robust construct validity, with fit indices satisfying standard thresholds (CFI ≥ 0.90, TLI ≥ 0.90, RMSEA ≤ 0.08). Stricter cutoffs (CFI ≥ 0.95; RMSEA ≤ 0.06) indicate excellent fit, but are not always required (Hu & Bentler, 1999; Kline, 2016).

Standardized factor loadings (e.g., ≥ 0.50; (≥ 0.70 preferred)) were statistically significant ($p < .001$), confirming convergent validity (Fornell & Larcker, 1981; Kline, 2016; Hair et al., 2019), while low cross-loadings supported discriminant validity across WBL dimensions. These psychometric evaluations ensured that the WBL measures reliably captured experiential, reflective, and collaborative learning constructs central to the theoretical framework underpinning the WBL–ACD symbiotic model.

Standardization and Scaling of ACD Measures

Adult Cognitive Development (ACD) indicators, literacy, numeracy, and adaptive problem-solving (APS) were obtained from OECD's PIAAC 2023 plausible value datasets. Five plausible values per domain were standardized (mean = 0, SD = 1) to enable cross-country and subgroup comparisons. Composite cognitive scores were computed by averaging plausible values,

consistent with OECD methodology. This standardization ensured comparability across demographic, occupational, and sectoral groups while preserving population-level variance. Scaling and transformation procedures aligned with PIAAC's proficiency-level framework, allowing interpretation of WBL–ACD linkages in both statistical and educationally meaningful terms within the SEM-Informed Static Policy Optimization analytical design.

Missing Data Handling

Missing data are carefully handled to preserve analytic integrity while minimizing bias. For SEM analyses, multiple imputation using predictive mean matching (PMM) is employed to account for missing values under the assumption of missing at random (MAR), generating five imputed datasets, which were subsequently pooled for estimation. This approach maintained parameter stability and valid standard errors. For static policy optimization that requires complete state-action sequences, listwise deletion was applied to ensure computational consistency and to avoid the propagation of uncertainty across learning episodes. Sensitivity analyses compared imputed and complete-case models, confirming negligible differences in key WBL–ACD parameter estimates and simulation convergence behavior.

Data Analysis Procedures

Data Cleaning and Organization

The initial data cleaning tasks are performed on the raw data table from the public-use data files. The PIAAC PUF file for 2023 US data has approximately 4573 participants (who completed the full household survey). The process involved creating distinct raw datasets with the required variables for each research question. Once the data files for each research question were segregated, they underwent thorough cleaning through several steps:

(1) Assess data quality - The data were reviewed and checked for inconsistencies, missing values, and errors. Standardized statistical tools were used to generate summary statistics, enabling the identification of patterns, trends, and potential outliers. Data quality metrics are listed to ensure accuracy, completeness, consistency, and timeliness of the data.

(2) Addressing missing metrics- Missing data, if present, were identified and handled depending on the data type (e.g., binary = logistic regression imputation, ordinal = ordered logistic imputation, nominal = multinomial logistic, and continuous = PMM). For indices, the missing values were handled using mode imputation if the missingness is very low (< 2–3%).

(3) Removing duplicates - Similarly, duplicate data points, if identified, are removed, ensuring that there is no loss of valuable information or introduction of skewness in the dataset.

(4) Correcting errors and inconsistencies is crucial, as checking for data distributions is essential when conducting distribution-dependent analysis, including parametric or non-parametric tests. We identified the problems in the data (multicollinearity, heteroscedasticity, autocorrelation, overfitting, excluding essential predictor variables, missing data, and issues with sample size and power) and fixed them to obtain a clean dataset.

Data Analysis

The data analysis process involves the use of both basic and advanced data analysis. Statistical analysis includes descriptive analysis and feature selection from the dataset to understand the nature and specific patterns in the data, informing the advanced data analysis process. This analysis was performed using SPSS version 29. The more advanced data analysis,

involving artificial intelligence (AI), includes running the integrated SEM and static policy optimization model, known as SEM-Informed Static Policy Optimization. The advanced analysis was performed using R version 4.6.1. The analysis tools have been explained below in detail:

Statistical-Based Data Analysis

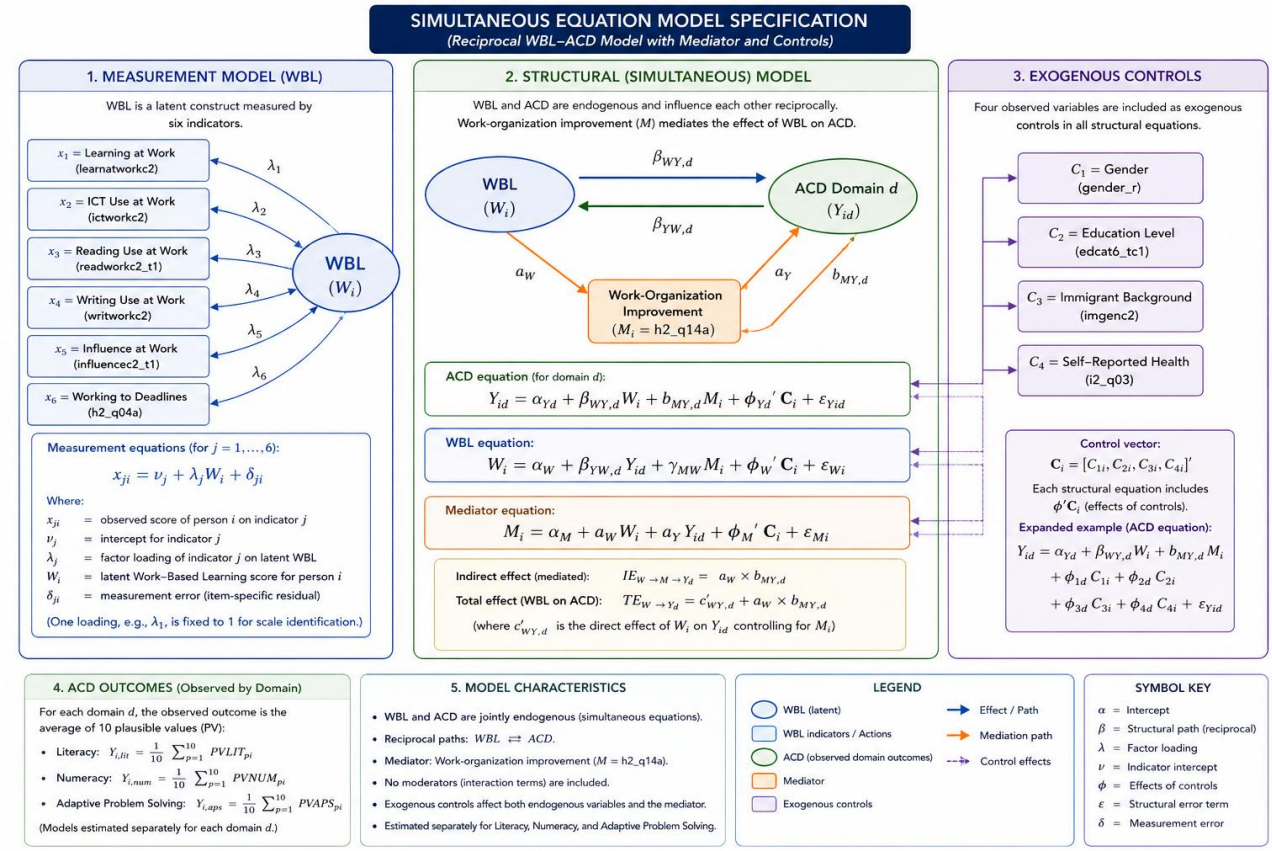
Descriptive Statistics

The descriptive analysis summarized the data characteristics and identified interesting patterns/trends that might be useful in exploring the research questions. For example, examining literacy, numeracy, and adaptive problem-solving across various occupations and roles differentiated through a range of socio-economic variables.

Structural Equation Modeling (SEM)

SEM, including a simultaneous equation modeling approach, is used to examine the reciprocal and interdependent relationship between WBL and ACD. SEM has been selected for the study because it allows the estimation of bidirectional causal pathways among multiple latent and observed constructs. The study also included mediating mechanisms, as well as control factors influencing both sides of the relationship. This approach captures the symbiotic feedback loop through which WBL activities enhance cognitive competencies and cognitive proficiency, which, in turn, reinforces engagement in workplace learning.

Figure 3-6 Summary of the SEM Equations



The model specifications (Figure 3-6) include two simultaneous structural equations:

Let W_i represent the latent work-based learning construct for individual i, and let Y_{id} represent the ACD outcome for domain d, where:

$$\boldsymbol{d} \in \{\boldsymbol{Literacy, Numeracy, Adaptive\ Problem\ Solving}\} \ldots\ldots\ldots \textbf{Equation 3-2}$$

Because the three ACD domains are analyzed separately, the reciprocal system is estimated three times, once for each domain.

In the case of the WBL measurement model, for the full WBL specification, the six observed indicators are related to the latent WBL construct as follows (Bollen, 1989; Kline, 2023; Byrne, 2016):

$$\boldsymbol{x_{ji} = \vee_j + \lambda_j W_i + \delta_{ji}} \ldots\ldots\ldots \textbf{Equation 3-3}$$

x_{ji} Observed score for person i on WBL indicator j. For example, it could be that person's score on Learning at Work, ICT Use at Work, or Working to Deadlines.

$\vee_j$ Intercept for indicator j. It represents the expected value of that indicator when the latent WBL factor equals zero.

λ_j Factor loading for indicator j. It shows how strongly that observed item reflects the latent WBL construct. A larger loading means the item is more strongly associated with WBL.

W_i Latent Work-Based Learning score for person i. It is not directly observed. It is estimated from the six WBL indicators.

δ_{ji} Measurement error or item-specific residual for person i on indicator j. It captures the part of the observed item that is not explained by the latent WBL factor.

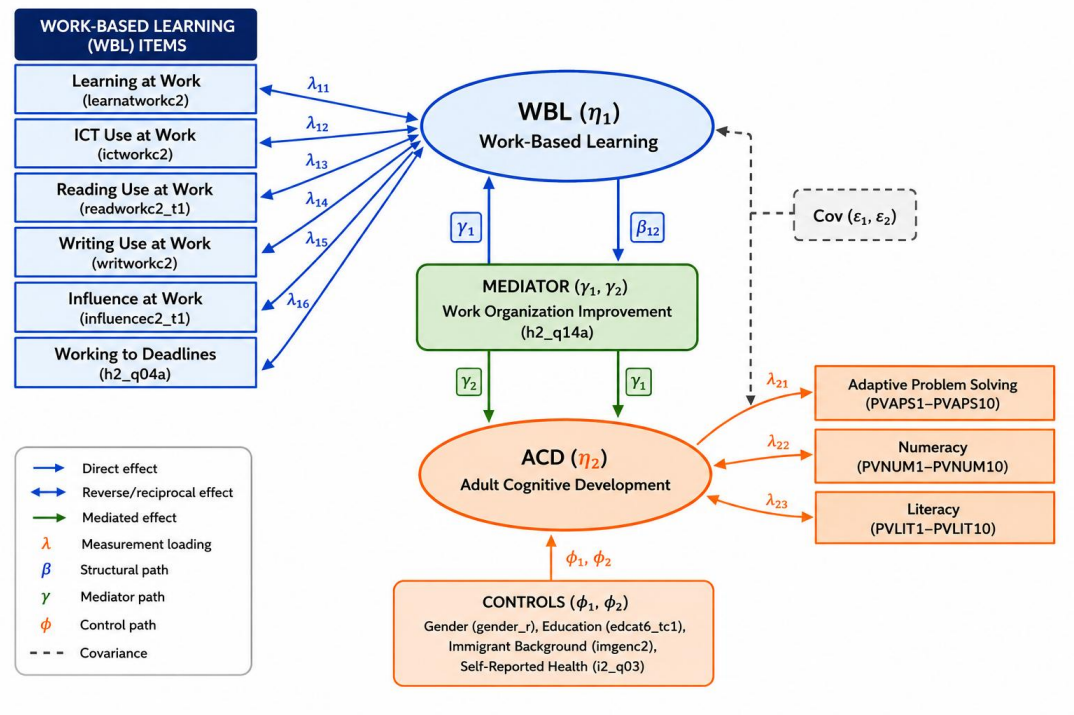
i, j The subscripts mean i identifies the individual or respondent, and j identifies the observed WBL indicator.

Both equations are jointly estimated using Full Information Maximum Likelihood (FIML) within a non-recursive SEM structure that statistically identifies mutual causation between WBL and ACD by including unique exogenous instruments and correlated disturbances.

The model is estimated using R (lavaan package), applying standardized path coefficients (β) to ensure comparability across constructs. Model fit was evaluated using the following conventional indices that include: (1) Comparative Fit Index (CFI), (2) Tucker-Lewis Index (TLI), (3) Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

Significant reciprocal paths between WBL and ACD confirm the hypothesized symbiotic relationship (Figure 3-7). However, mediation effects illuminate the mechanisms under which WBL contributes to ACD and vice versa.

Figure 3-7 Statistical Path Diagram for the Simultaneous Equation Model of the Proposed Symbiotic WBL-ACD Nexus



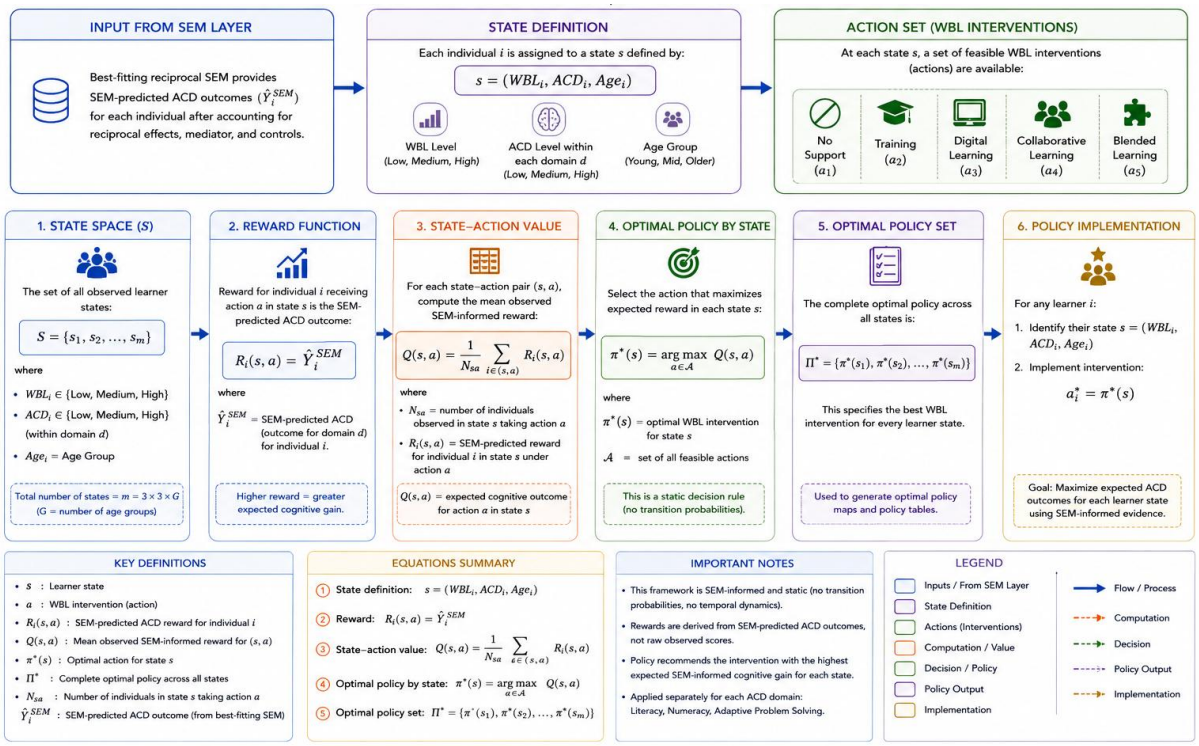
Artificial-Intelligence (AI) Based Data Analysis

SEM – Informed Static Policy Optimization as an AI-Informed Ex-Post Evaluation Framework

The AI-informed component of this study is operationalized through the SEM-informed static policy optimization framework (Figure 3-8). Instead of treating SEM itself as an artificial intelligence technique, the framework uses estimates derived from the empirical modeling stage to support automated, state-specific decision-making. Following ex-post estimation of the WBL-ACD relationships using observed PIAAC data, adults are classified into empirical WBL-ACD states, alternative workplace-learning strategies are evaluated within those states using survey-

weighted state-action rewards informed by the SEM estimates, and the strategy associated with the highest estimated reward is identified for each state. In this way, the framework converts retrospective empirical evidence into systematic, data-driven decision recommendations. The AI-informed element therefore resides in the computational decision-support and optimization process rather than in the SEM estimation itself. Following the estimation of the reciprocal structural equation models, the best-fitting SEM was used to develop a static policy optimization framework for identifying evidence-based work-based learning (WBL) interventions that maximize adult cognitive development (ACD).

Figure 3-8 SEM Informed Static Policy Optimization Framework



Unlike traditional reinforcement learning, which estimates state-action values through iterative temporal-difference learning and Bellman recursion, the proposed approach derives policy recommendations directly from empirically observed data and SEM-predicted cognitive

outcomes. Consequently, the framework is referred to as SEM-informed static policy optimization, reflecting its reliance on structural equation modeling to estimate intervention rewards rather than learning through repeated interaction with an environment.

The optimization framework begins by defining a finite set of learner states. Each state represents a unique combination of an individual's work-based learning level, adult cognitive development level, and age group. Formally, each state is defined as:

$$\boldsymbol{S} = (\boldsymbol{WBL_i}, \boldsymbol{ACD_{i,}}, \boldsymbol{Age_i}), \ldots\ldots\ldots\ldots \textbf{Equation 3-4}$$

Where, WBL_i denotes the individual's work-based learning level (low, medium, or high), ACD_i denotes the corresponding cognitive development level within a given domain, and Age_i represents the individual's age category. The complete collection of learner states forms the state space,

$$\boldsymbol{S} = \{\boldsymbol{s_1}, \boldsymbol{s_2} \ldots\ldots\ldots\ldots, \boldsymbol{s_m}\} \ldots\ldots\ldots\ldots \textbf{Equation 3-5}$$

where m denotes the total number of observed states.

For each learner state, a finite set of feasible work-based learning interventions was defined. These interventions constitute the available action space,

$$A = \{No\ support, Training, Digital\ Learning, Collaborative\ Learning, Blended\ Learning\},$$

$$\ldots\ldots\ldots\ldots\ldots \textbf{Equation 3-6}$$

representing practical instructional strategies that can be implemented within workplace learning environments.

The reward associated with each intervention was derived from the reciprocal structural equation model rather than directly from observed cognitive scores. Specifically, the SEM generates a predicted cognitive outcome for each individual after accounting for reciprocal effects, mediation, and exogenous control variables. Let $\hat{Y}_i^{SEM}$ denote the SEM-predicted

cognitive outcome for participant - $'i'$.The reward associated with action $a$in state $s$is therefore defined as

$$\boldsymbol{R_i\,(s,a) = \ \widehat{Y}_i^{SEM}}\ \textbf{……..\ Equation 3-7}$$

Accordingly, larger reward values indicate interventions that are expected to produce greater improvements in adult cognitive development according to the estimated structural model.

Instead of estimating transition probabilities between learner states, the proposed framework computes the value of each state-action pair directly from empirical data. For every observed state-action combination, the state-action value is calculated as the mean SEM-informed reward across all individuals belonging to that state and receiving the corresponding intervention. This value is defined as

$$\boldsymbol{Q\ (s,a)\ = \frac{1}{N_{sa}} \sum_{i\in(s,a)} R_i(s,a)}\textbf{…….\ Equation 3-8}$$

Where N_{sa} denotes the number of individuals observed in state 's' under action a. Consequently, Q (s, a) represents the expected cognitive outcome associated with implementing intervention 'a' for learners occupying state 's'.

The optimal intervention for each learner state is determined by selecting the action that maximizes the corresponding state-action value. The optimal policy is therefore defined as

$$\pi^*(s)\ =\ arg\ max_{a\epsilon A}\ Q(a,s),$$

Where $\pi^*(s)$ denotes the recommended intervention for state s. Applying this decision rule across all learner states produces the complete static policy,

$$\prod* = \{\boldsymbol{\pi^*(s_1), \pi^*(s_2), \ldots\ldots \pi^*(s_m)}\}\textbf{……\ Equation 3-9}$$

which specifies the intervention expected to maximize adult cognitive development within each observed learner state.

Because the proposed framework estimates state-action values directly from empirical SEM-informed rewards, it differs fundamentally from traditional Q-learning. There is no Bellman recursion, temporal-difference updates, exploration-exploitation mechanism, or iterative value-function approximation employed. Instead, policy recommendations are obtained through direct optimization of empirically estimated SEM-based rewards, making the framework particularly suitable for cross-sectional observational data where repeated interactions with an environment cannot be observed. The resulting policies therefore represent evidence-based recommendations that maximize expected adult cognitive development under the estimated reciprocal relationships between work-based learning and cognitive outcomes.

Integration of SEM and Static Policy Optimization

The analytical framework integrates SEM with SEM-informed static policy optimization to provide complementary perspectives on the Work-Based Learning (WBL) and Adult Cognitive Development (ACD) nexus. SEM addresses the first research question by estimating the reciprocal structural relationships between WBL and ACD while accounting for mediating and exogenous variables. Building on these structural estimates, the static policy optimization framework addresses the second research question by identifying the work-based learning strategy associated with the highest expected cognitive outcome for each empirical WBL-ACD state. Rather than serving as a separate validation procedure, the optimization framework translates the structural findings from SEM into evidence-based, state-specific intervention recommendations. Together, these complementary analyses strengthen the study by combining associational explanation with practical decision support, thereby providing both theoretical insights into the reciprocal WBL-ACD relationship and actionable guidance for optimizing workplace learning interventions.

Modeling Strategy

The modeling approach follows a three-tiered structure:

- Directional Structure Testing (Core SEM logic)
- Measurement Sensitivity (Observed vs Latent WBL)
- Identification & Robustness Assessment (Alternative Reciprocal SEM Specifications and 2SLS Robustness)

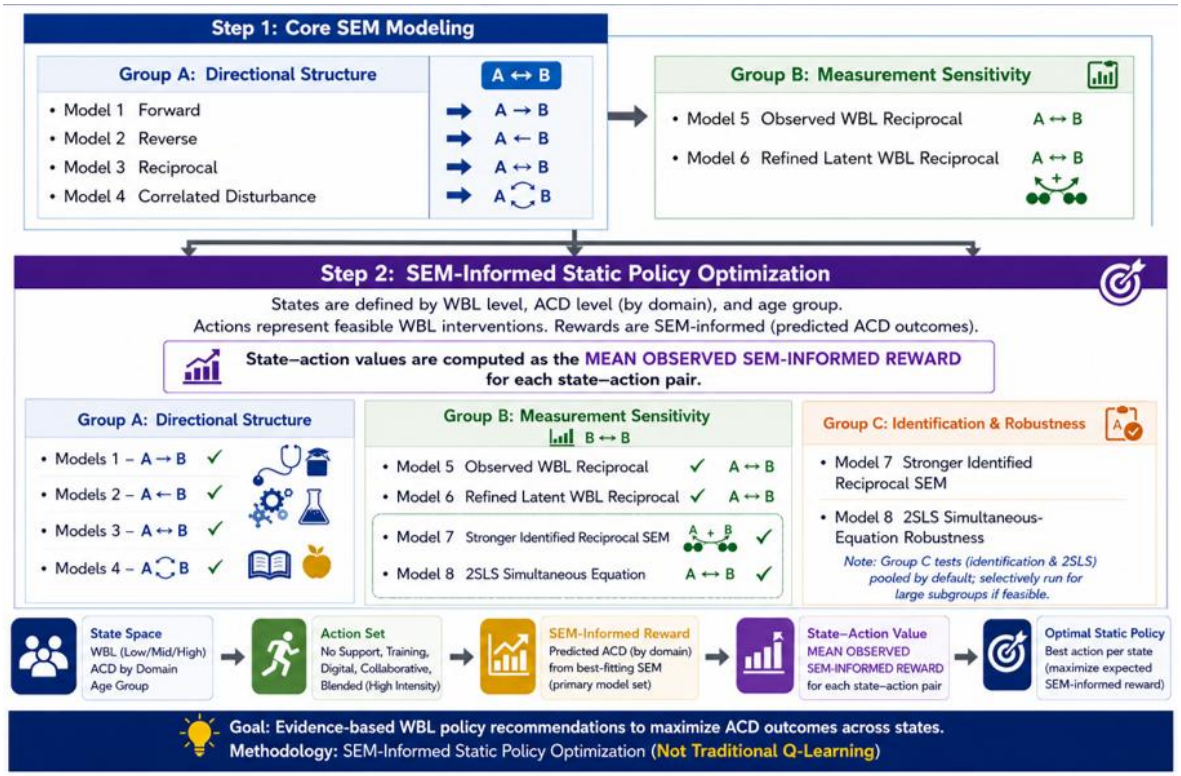
These analytical components collectively establish the structural validity and robustness of the reciprocal WBL-ACD relationship before informing the policy optimization stage.

Figure 3-9 summarizes the overall modelling strategy adopted in this study, integrating Simultaneous Equation Modelling (SEM) with SEM-informed static policy optimization to identify evidence-based work-based learning (WBL) strategies associated with improved Adult Cognitive Development (ACD). The framework consists of two sequential stages. The first stage establishes the reciprocal structural relationships between WBL and ACD through a series of progressively more rigorous SEM specifications. The second stage translates these structural findings into a static decision-support framework that identifies the work-based learning intervention associated with the highest SEM-informed mean observed reward for each empirical learner state.

The first stage evaluates the reciprocal association between WBL and ACD through progressively more rigorous SEM specifications. Group A examines alternative directional structures by estimating forward (Model 1), reverse (Model 2), reciprocal – exploratory non recursive (Model 3), and correlated disturbance (Model 4) models to determine the most appropriate representation of the relationship between WBL and ACD. Model 3 was estimated to examine the statistical interdependence between WBL and ACD within a non-recursive SEM

framework. Because reciprocal models are sensitive to identification in cross-sectional data, their findings were interpreted alongside recursive SEMs (Model 1 and Model 2 and instrumental-variable robustness analyses. Group B assesses measurement sensitivity by comparing reciprocal SEMs based on observed WBL indicators (Model 5) and a latent WBL construct (Model 6). Together, these models evaluate the robustness of the reciprocal WBL-ACD relationship across alternative structural assumptions and measurement specifications.

Figure 3-9 Modeling Strategy for SEM Informed Static Policy Optimization



Rather than assuming a single direction of association in advance, the study compared several competing models representing different explanations of how WBL and ACD may be related.

Table 3-10 Competing Model Specifications Used to Evaluate the WBL-ACD Associations

Model	Specification	Primary purpose
Model 1	Forward Recursive Mediation	Tests the hypothesized WBL → ACD direction, including the mediating pathway through reflection/improvement of work processes.
Model 2	Reverse	Tests alternative directional specification ACD → WBL.
Model 3	Reciprocal Latent	Estimates WBL → ACD and ACD → WBL simultaneously using latent WBL.
Model 4	Correlated Disturbance	Examines shared unexplained covariance between WBL and ACD without requiring reciprocal structural effects.
Model 5	Reciprocal Observed-WBL	Tests reciprocal paths using an observed WBL composite rather than the latent WBL construct.
Model 6	Reciprocal Refined Latent-WBL	Tests reciprocal paths using the reduced/refined WBL measurement specification as a measurement sensitivity analysis.
Model 7	Reciprocal Model with Exclusion Restrictions	Estimates reciprocal paths with explicit identification restrictions: EDCAT6_TC1 predicts ACD but is excluded from the WBL equation; NFEEVER predicts WBL but is excluded from the ACD equation.
Model 8	2SLS Robustness Model	Evaluates directional relationships using a two-stage least-squares specification as an additional identification/robustness analysis.

The second stage implements SEM-informed static policy optimization using the best-performing SEM specification. Individuals are classified into empirical states defined by WBL level, ACD level within each cognitive domain, and age group. Feasible WBL interventions constitute the action set, and state-action values are computed as the mean observed SEM-informed reward for each state-action combination. The optimal static policy selects the work-based learning intervention associated with the highest expected reward for each empirical state. To further evaluate the stability of the findings, Group C incorporates a more strongly identified reciprocal SEM (Model 7) and a two-stage least squares simultaneous equation model (Model 8) as robustness analyses. Model 7 was estimated as an alternative reciprocal specification using exclusion restrictions. The 2SLS model was used as a robustness check rather than definitive causal identification. Its results were evaluated alongside the recursive SEMs and the 2SLS robustness analysis to assess the consistency of the reciprocal association. Agreement across

these specifications provides additional confidence that the recommended WBL strategies are not dependent on a single modeling approach. Rather than relying on iterative reinforcement learning or transition probability estimation, the framework computes a state-action value for every state-action combination as the mean observed SEM-informed reward, providing an empirical estimate of the expected cognitive outcome associated with each intervention.

To evaluate the stability of the findings, the policy optimization framework is complemented by additional robustness analyses. Models 1 through 6 are retained to verify consistency across alternative causal structures and measurement approaches, while Model 7 employs a strongly identified reciprocal SEM and Model 8 applies two-stage least squares (2SLS) simultaneous-equation estimation to address potential endogeneity. Collectively, these analyses assess whether the estimated policy recommendations remain stable across increasingly rigorous model specifications.

The lower workflow illustrates the sequence through which optimal policies are derived. State definitions are combined with feasible intervention actions and SEM-derived rewards to estimate state-action values for each state-action pair. The intervention yielding the highest mean observed SEM-informed reward is then selected as the optimal static policy for that learner state. Because the procedure relies entirely on empirical SEM predictions rather than iterative value updating, Bellman recursion, or exploration-exploitation mechanisms, the proposed framework constitutes a SEM-informed static policy optimization approach rather than traditional Q-learning. The resulting policies provide evidence-based recommendations for maximizing adult cognitive development through targeted work-based learning interventions.

Diagnostics & Reporting

Diagnostic checks were conducted to ensure that the simultaneous equation estimates and policy recommendations were statistically robust and theoretically interpretable. The primary SEM models were estimated using robust maximum likelihood (MLR) with sampling weights and full-information maximum likelihood (FIML) for incomplete data. Additional robustness analyses included identified reciprocal SEM, two-stage least squares (2SLS), plausible-value sensitivity analyses, multiple-imputation sensitivity analyses, Fay's balanced repeated replication (BRR), and bootstrap evaluation of policy stability. Tables 3-9 and 3-10 summarize the diagnostic procedures and evaluation criteria adopted in this study.

SEM Diagnostics and Thresholds

Diagnostic checks covering identification, endogeneity, instrument validity, model fit, and parameter stability ensure that the simultaneous equation estimates of the WBL–ACD nexus are both statistically sound and theoretically interpretable. Table 3.10 summarizes diagnostics and their respective thresholds for SEM.

Table 3-11 Diagnostics and Thresholds for Simultaneous Equation Modeling (SEM)

Diagnostic Category	Indicator	Decision Criterion	Purpose
Model Fit	CFI, TLI, RMSEA, SRMR	CFI/TLI ≥ .90 (≥ .95 preferred); RMSEA ≤ .08; SRMR ≤ .08	Evaluates overall model fit (Hu & Bentler, 1999; Kline, 2023).
Model Convergence	lavaan convergence	Successful convergence with no inadmissible estimates	Ensures the SEM solution is estimable (Kline, 2023).
Structural Parameters	Standardized path coefficients	Theory-consistent sign and $p < .05$	Evaluates reciprocal WBL–ACD relationships.
Reliability	Cronbach's α, McDonald's ω	α, ω ≥ .70	Assesses internal consistency of WBL indicators (Hair et al., 2019).
Model Robustness	Alternative SEM specifications (Models 1–7)	Stable direction and significance of key paths	Evaluates sensitivity to alternative structural assumptions.

Diagnostic Category	Indicator	Decision Criterion	Purpose
Identification Robustness	Model 7	Stable reciprocal coefficients	Verifies stronger identification through exclusion restrictions.
Econometric Robustness	Model 8 (2SLS)	Consistent coefficients with HC1 robust standard errors	Confirms findings using instrumental-variable estimation.
Survey & Measurement Robustness	Plausible values, Multiple Imputation, Fay-BRR replicate weights	Stable estimates across analyses	Evaluates robustness to measurement uncertainty, missing data, and complex survey design.

SEM-Informed Static Policy Optimization Diagnostics and Thresholds

SEM-informed static policy optimization diagnostics in Table 3.8 evaluated the robustness and stability of state-specific policy recommendations through assessment of reward estimation, policy consistency, and sensitivity analyses. Robustness was examined using survey-weighted reward estimation, bootstrap policy stability, plausible-value analyses, and alternative SEM specifications to ensure that the recommended work-based learning (WBL) strategies were stable, interpretable, and theoretically consistent. These diagnostic procedures enabled the policy optimization framework to complement the structural modeling of the WBL-ACD nexus by translating reciprocal SEM findings into evidence-based, state-specific intervention recommendations.

Table 3-12 Diagnostics and Thresholds for SEM-Informed Static Policy Optimization

Diagnostic Category	Indicator	Decision Criterion	Purpose
State Construction	Empirical WBL–ACD tertiles	Consistent state classification	Defines comparable learner states for policy optimization.
Reward Estimation	Survey-weighted SEM-informed mean observed reward	Estimated for every state-action pair	Quantifies expected cognitive outcomes associated with each WBL action.
Reward Stabilization	Shrinkage toward state mean	Applied to sparse state-action cells	Improves stability of reward estimates.

Diagnostic Category	Indicator	Decision Criterion	Purpose
Policy Selection	Static optimal policy	Highest SEM-informed reward within each state	Identifies the recommended WBL intervention for each learner state.
Policy Robustness	Bootstrap stability (250 resamples), Plausible values, Models 3, 7 & 8	Consistent optimal actions across analyses	Evaluates robustness and reproducibility of policy recommendations.

Integrated Diagnostics and Thresholds SEM-Informed Static Policy Optimization

The overall analytical framework was evaluated by integrating evidence from both analytical stages. The SEM component established reciprocal structural relationships between WBL and ACD, while the SEM-informed static policy optimization framework translated these relationships into state-specific intervention recommendations. Integration was assessed by examining whether policy recommendations remained consistent across alternative SEM specifications (Models 3, 5, 6, 7, and 8), plausible values, bootstrap samples, and complex survey estimation procedures. Consistency across these analyses provided evidence that the recommended WBL strategies were robust to alternative structural assumptions and estimation methods.

Ethical Considerations

Several ethical considerations arise due to the application of simulation analysis of the PIAAC dataset, even though using the public-use files: (a) de-identifying the participants so that they cannot be re-identified through linking their other datasets;(b) making cautious interpretation of the analysis results, ensuring models do not overstate relationships from the observational survey data. Since PIAAC is cross-sectional data, it might not fully capture the learning pathways of the adults; (c) careful bias estimation by clarifying state definitions, action categories, and reward metrics is essential, as these metrics may have variable impacts on

vulnerable demographic or socio-economic groups; (d) a clear description of methodology and detailing every assumption in the modeling approach is critical so that findings are replicable. Additionally, in the results section, the findings must be presented in a distinct manner, highlighting the key revelations without compromising the integrity of any vulnerable groups. The study's conclusions particularly focus on policy implications that drive learning opportunities from the symbiotic WBL-ACD nexus, and further opportunities that enhance quality learning prospects for adults.

Limitations of the Methods

This study utilizes the 2023 Programme for the International Assessment of Adult Competencies (PIAAC) public-use dataset and integrates Simultaneous Equation Modeling (SEM) with SEM-informed static policy optimization to examine the reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). While this integrated framework provides both explanatory and decision-support capabilities, several methodological limitations should be acknowledged.

First, the cross-sectional nature of the PIAAC survey limits the ability to establish temporal causality. Although reciprocal relationships between WBL and ACD are estimated using simultaneous equation models, the findings should be interpreted as evidence of reciprocal associations rather than definitive causal effects over time. To strengthen causal interpretation, the study estimates multiple alternative SEM specifications, including an identified reciprocal SEM and instrumental-variable (2SLS) models, while incorporating relevant demographic and educational control variables to reduce potential endogeneity and omitted-variable bias.

Second, measurement uncertainty inherent in large-scale assessment data may influence estimates of adult cognitive development. To address this limitation, the analyses incorporate all

ten plausible values for literacy, numeracy, and adaptive problem solving, multiple imputation for missing data, and Fay's balanced repeated replication (BRR) weights to account for the complex PIAAC sampling design. These robustness analyses evaluate the stability of parameter estimates across alternative representations of the data.

Third, the SEM-informed static policy optimization framework is based on observed cross-sectional state-action relationships rather than longitudinal behavioral trajectories. Consequently, the framework identifies evidence-based work-based learning strategies associated with the highest expected cognitive outcomes for each empirical learner state but does not model sequential adaptation or long-term learning dynamics. To improve the reliability of policy recommendations, survey-weighted reward estimation, shrinkage of sparse state-action cells, bootstrap policy stability analyses, and sensitivity analyses across alternative SEM specifications are employed. These procedures ensure that the recommended interventions remain stable and interpretable under varying model assumptions. Finally, the findings are derived from employed adults in the United States participating in PIAAC 2023 and should therefore be generalized cautiously to other countries, workforce populations, or institutional contexts. Future research using longitudinal data and repeated workplace assessments could extend the proposed framework to evaluate how work-based learning interventions influence adult cognitive development over time.

Collectively, these mitigation strategies enhance the robustness, transparency, and interpretability of the findings while ensuring that the integrated SEM and SEM-informed static policy optimization framework remains appropriate for survey-based analyses of workplace learning and adult cognitive development.

Chapter Summary

This study adopts a quantitative research approach, applying a quasi-experimental modeling framework to examine the reciprocal relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) using the 2023 U.S. PIAAC dataset. The study integrates simultaneous equation modeling (SEM) with SEM-informed static policy optimization to investigate both the bidirectional association between WBL and ACD and the workplace-learning actions associated with the highest expected cognitive outcomes across observed learning states.

The analytical framework combines reciprocal SEM and static policy optimization. The SEM component estimates the structural relationships linking workplace learning experiences, including learning at work, ICT use, and influence over work activities, with adult cognitive development while accounting for reciprocal effects, mediation through workplace reflection, and relevant exogenous control variables. Building on these findings, the SEM-informed static policy optimization component evaluates alternative workplace-learning actions using empirically observed state-action rewards to identify the action associated with the highest expected cognitive outcome within each observed WBL-ACD state. Together, these approaches provide complementary evidence by explaining the reciprocal structure of workplace learning and cognitive development while identifying evidence-based workplace-learning strategies for employed adults.

Ethical considerations include protecting participant confidentiality, avoiding re-identification, interpreting observational findings cautiously, ensuring transparent reporting, and acknowledging the limitations of secondary survey data. Methodological limitations include the cross-sectional nature of the PIAAC dataset, the inability to establish temporal causality,

potential simultaneity bias, and unobserved heterogeneity. These limitations were addressed through reciprocal SEM, multiple imputations for missing data, psychometric evaluation of the workplace learning construct, and robust model diagnostics. Collectively, these methodological decisions strengthen the validity, transparency, and policy relevance of the study's findings.

Chapter 4 - Results

Introduction

This chapter presents the empirical findings from the 2023 PIAAC analyses. The results are organized around the two research questions. First, the chapter examines the reciprocal association between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) across the domains of literacy, numeracy, and adaptive problem solving (APS) using simultaneous equation modeling (SEM). Second, it presents the findings from the SEM-informed static policy optimization framework, identifying the workplace-learning actions associated with the highest expected cognitive outcomes across observed WBL-ACD states.

The chapter begins by describing the analytical sample, data quality assessments, and the psychometric evaluation of the workplace learning construct, including missing data diagnostics, reliability, and construct validity. It then presents the SEM results, including model fit, parameter estimates, mediation effects, and robustness analyses. Finally, the chapter reports the results of the SEM-informed static policy optimization, including state-specific expected rewards, optimal workplace-learning actions, comparative action effects, and policy stability. Throughout the chapter, the findings are interpreted as evidence of reciprocal associations within a cross-sectional design rather than as definitive evidence of temporal causality, providing an empirically grounded basis for the discussion and practical implications presented in Chapter 5.

Analytic Sample Description and Data Quality

This section describes the derivation of the analytic sample from the 2023 U.S. PIAAC dataset and evaluates the quality of the data used for subsequent analyses. Before testing the research questions, the quality of the analytical data was evaluated in four stages. First, the derivation and composition of the analytical sample were examined. Second, the extent and

pattern of missing data were assessed. Third, the multiple-imputation procedure was evaluated to determine whether it produced plausible values without materially changing the original distributions or relationships among variables. Finally, the reliability and construct validity of the WBL measure were examined. Together, these analyses determine whether the data provides an adequate empirical foundation for the subsequent structural models. Figure 4.1 illustrates the analytic sample flow.

Figure 4-1 Derivation of the Final Analytical Sample

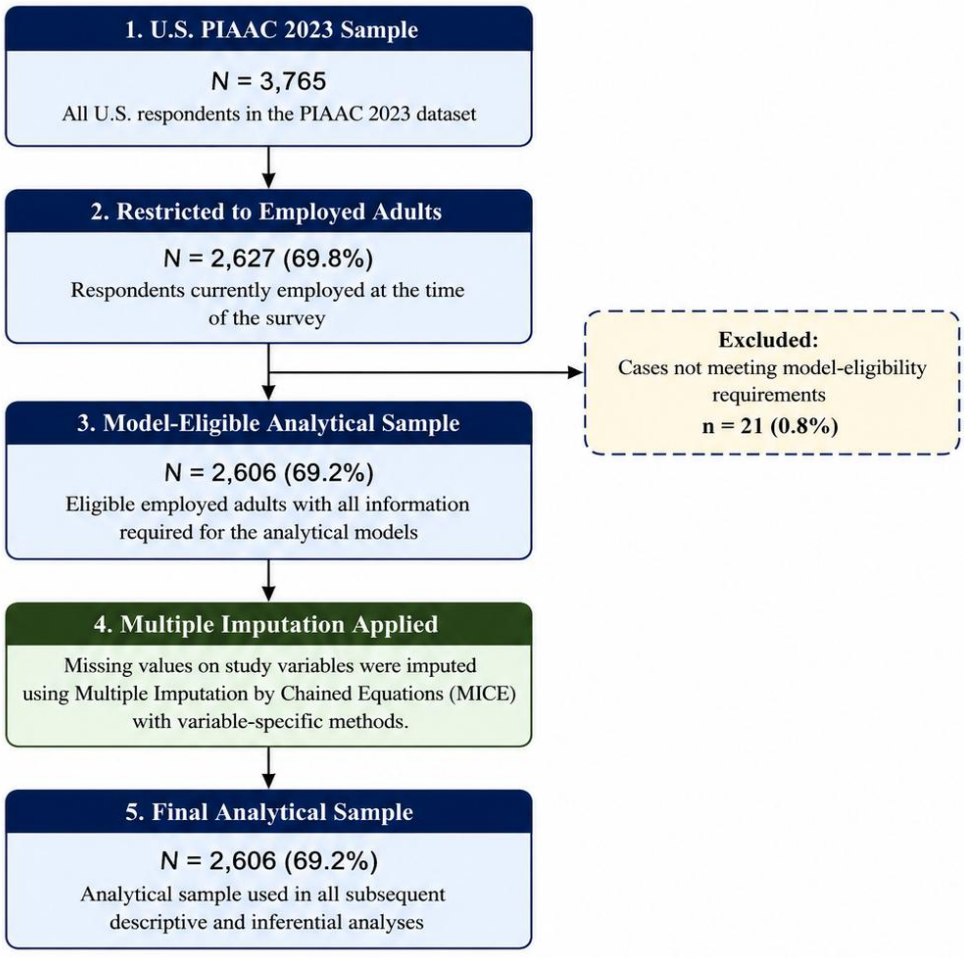


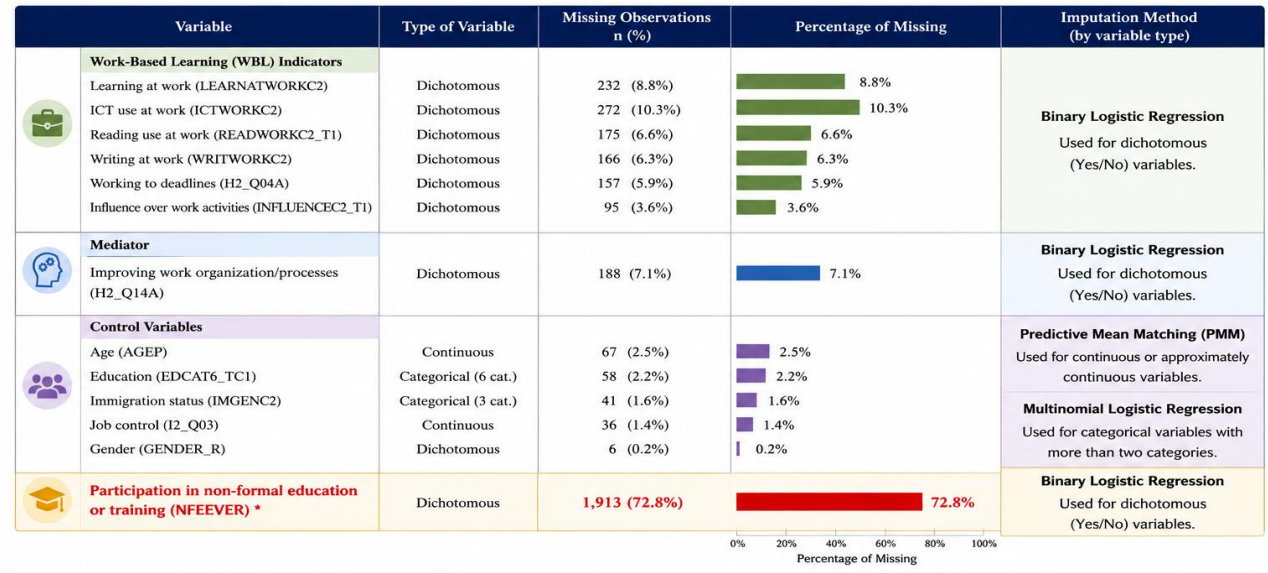
Figure 4-1 summarizes the derivation of the analytic sample from the 2023 U.S. PIAAC dataset. The original U.S. PIAAC 2023 dataset contained 3,765 respondents. The study restricted

the sample size to employed adults and produced an eligible employed sample of 2627 respondents (69.8% of the original sample). An additional 21 respondents did not meet the requirements for inclusion in the analytical models (e.g., missing key information required for model specification), resulting in a model-eligible analytical sample of 2606 (69.2% of the original sample). Multiple imputation was then used to address missing values within this sample. Therefore, the final analytical sample remained 2606 respondents.

Missing Data and Multiple Imputation

Prior to model estimation, patterns of missing data were evaluated to assess their potential impact on the analyses. Rather than excluding incomplete cases, an adaptive multiple imputation approach was implemented to preserve the analytical sample and minimize bias.

Figure 4-2 Missing Data Profile and Imputation Methods for Study Variables.



Note.

1. Abbreviations: WBL = Work-Based Learning; ICT = Information Communication Technology; NFEEVER = Participation in non-formal education or training; PMM = Predictive Mean Matching; MICE = Multiple Imputation by Chained Equations; ACD = Adult Cognitive Development.

2. Percentages are calculated out of the total U.S. PIAAC 2023 sample of employed adults before multiple imputation (N=2,627). NFEEVER has the highest proportion of missing data (72.8%). Results involving this variable should be interpreted with appropriate caution.
3. Imputation methods were selected according to the measurement level of each variable to generate plausible values and preserve the underlying distributional properties. The dichotomous variable underwent binary logistic regression, the continuous or near-continuous variables underwent PMM, and the categorical variables (>2 categories) underwent multinomial logistic regression.
4. Multiple imputation by chained equations (MICE) with 50 imputed datasets was used to handle missing data. The imputation model included all study variables, demographic and employment characteristics, and plausible values for the ACD domains. This approach retained available information and avoided additional loss of cases due solely to item-level missingness.

Figure 4-2 summarizes the extent of missing data and the adaptive imputation methods applied to the selected PIAAC 2023 variables. Most study variables exhibited relatively low levels of missingness, generally below 12%, with the exception of participation in non-formal education or training (NFEEVER). Thus, missingness was concentrated primarily in NFEEVER rather than being widespread across study variables. Given the extent of item-level missingness, particularly for NFEEVER, complete-case analysis could result in substantial loss of available information and potentially introduce bias. Multiple imputation was therefore used to retain available information while avoiding additional case loss due solely to missing responses.

An adaptive imputation strategy was used in which the imputation model was matched to the measurement level of each variable. Missing values were addressed using multiple imputation by chained equations (MICE), with imputation models matched to the measurement level of each variable. Predictive mean matching was applied to continuous or approximately continuous variables, binary logistic regression to dichotomous variables, and multinomial logistic regression to categorical variables with more than two categories. The MICE procedure generated multiple completed datasets; however, the primary analytic pipeline used the first completed dataset for model estimation and subsequent analyses. Accordingly, the primary

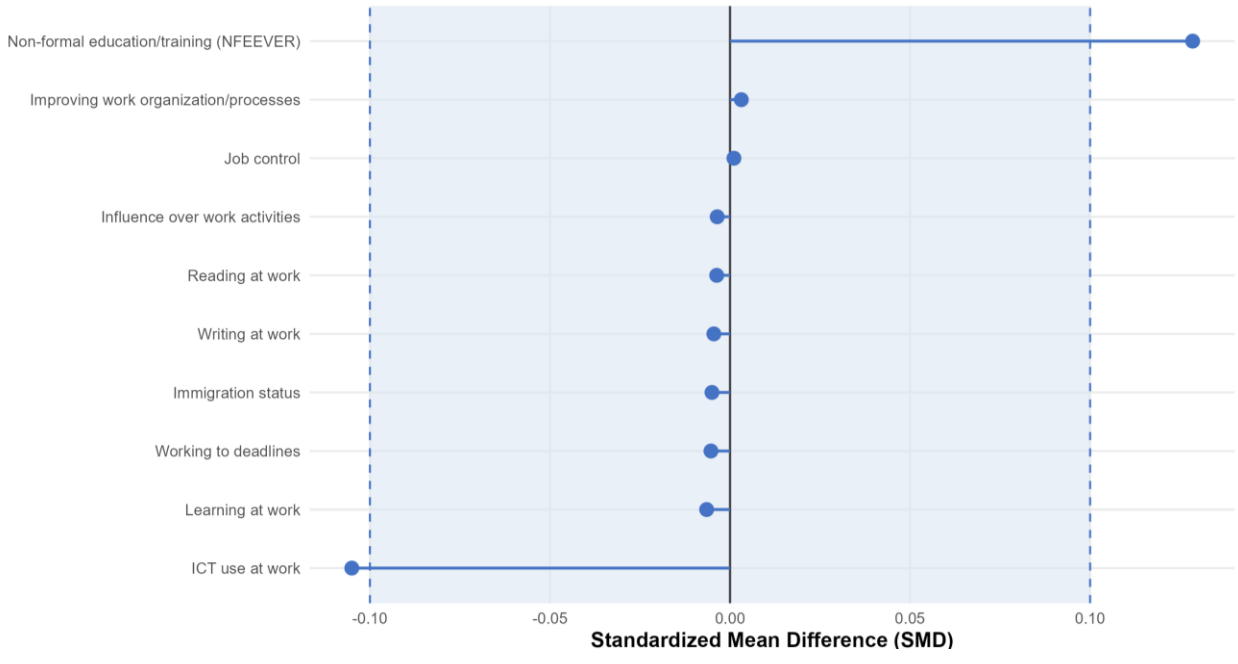
results should be interpreted as analyses of a multiply imputed completed dataset rather than as Rubin-pooled multiple- imputation estimates. The full imputation object was retained to permit pooled sensitivity analyses across imputations. The completed data were subsequently evaluated for distributional preservation, plausibility of imputed values, and preservation of relationships among variables. These diagnostics are presented in Figures 4-3 through 4-6.

Evaluation of the Imputation Procedure

Distribution Preservation

Distribution preservation was evaluated to determine whether the multiple imputation procedure maintained the original distributional characteristics of the study variables. Comparing the observed data before imputation with the completed data after imputation provides evidence that the imputation process did not introduce substantial distortion in the variables used for subsequent analyses.

Figure 4-3 Distribution Preservation Summary



Note.

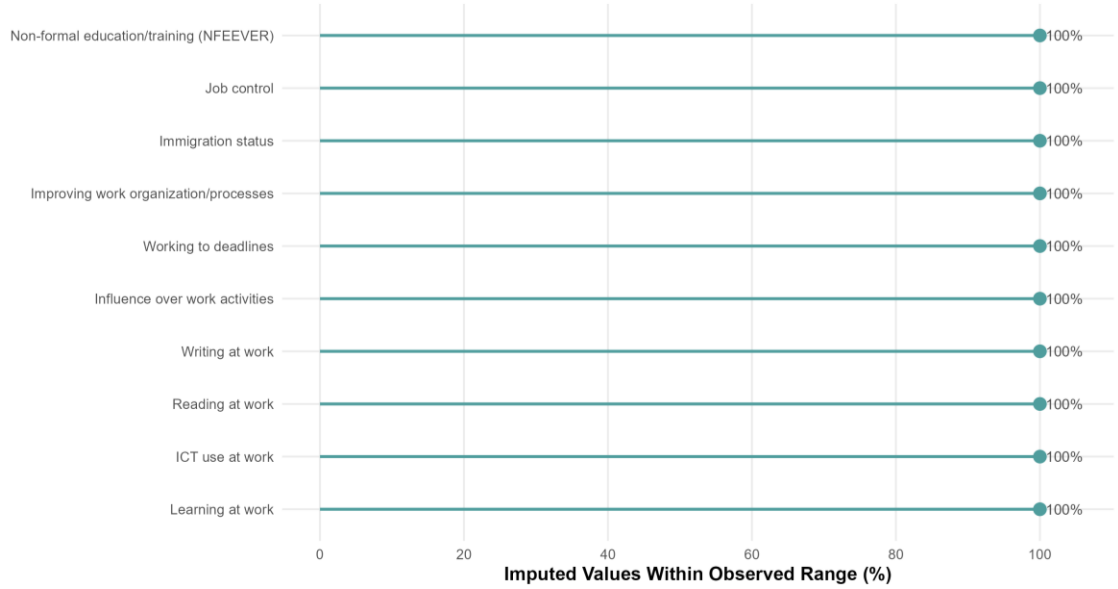
This figure shows the standardized mean differences between observed data and the completed dataset 1. Values closer to 0 indicate greater distributional similarity. The shaded region and dashed lines show ± 0.10 as a descriptive reference group.

The multiple-imputation procedure was first evaluated by examining whether completion of missing observations materially shifted the distributions of the study variables. Figure 4-3 presents standardized mean differences (SMDs) between the observed data and completed dataset 1, with values closer to zero indicating greater similarity in central tendency. An absolute SMD of 0.10 was used as a descriptive reference for identifying potentially meaningful distributional shifts. Most variables showed only minimal differences between the observed and completed data, with SMDs falling within the ±0.10 reference range. NFEEVER was the notable exception, with an SMD of 0.128, indicating a modest upward shift following imputation. Given NFEEVER's substantially higher initial missingness (72.8%), this difference was examined further through across-imputation and correlation-stability sensitivity analyses. Overall, Figure 4-3 indicates that imputation produced little change in the central tendencies of most study variables, while identifying NFEEVER as requiring additional sensitivity assessment.

Imputed Value Realism

Figures 4-4 and 4-5 assessed the plausibility of the imputed values. As shown in Figure 4-4, 100% of imputed values for all evaluated variables fell within their respective observed empirical ranges. Figure 4-5 further showed that 100% of imputed values for the five discrete variables, including NFEEVER, matched categories or codes present in the observed data.

Figure 4-4 Imputed Values Realism for Key Variables

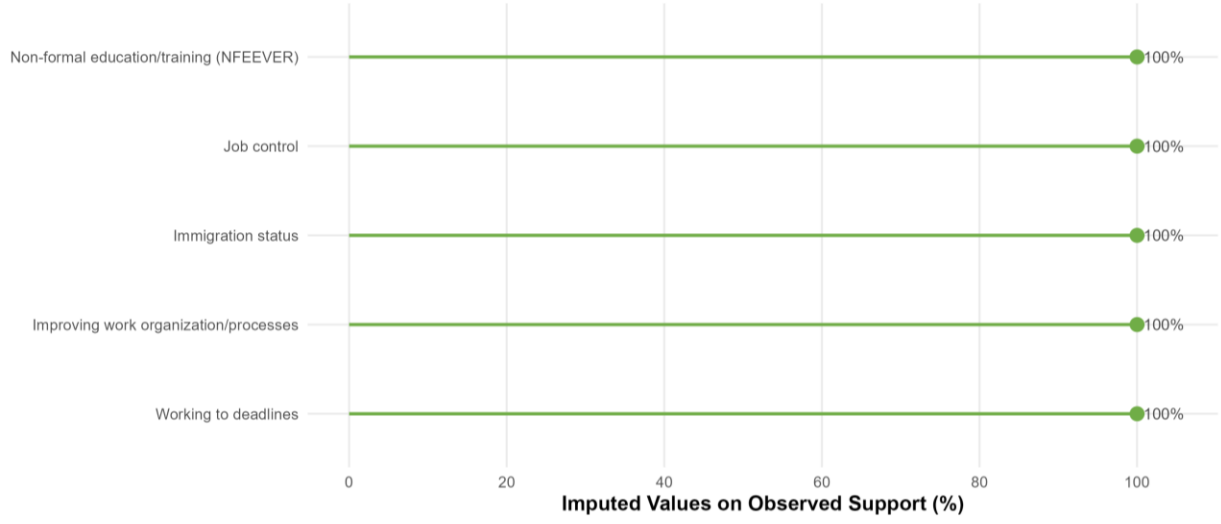


Note.

The figure shows the percentage of imputed values falling within the observed empirical range. Higher percentages indicate that imputed values remained within ranges represented in the observed data.

These results indicate that the imputation procedure did not generate out-of-range or unsupported values. However, these diagnostics assess the plausibility of individual imputed values rather than whether the observed distributions were fully preserved, which was evaluated separately in subsequent analyses.

Figure 4-5 Imputed Values Realism for Key Variables



Note.

The figure shows the percentage of imputed values falling within the observed empirical range. Higher percentages indicate that imputed values remained within ranges represented in the observed data.

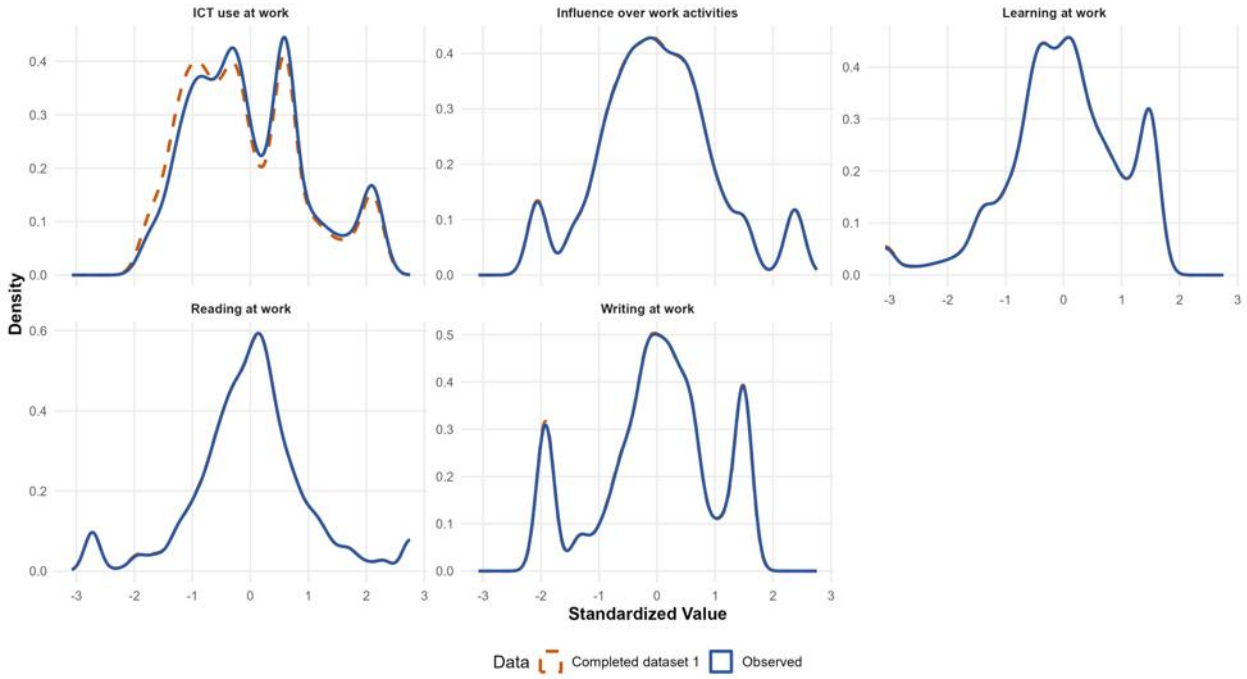
Standardized Overlay

Because the study variables are measured on different scales, standardized overlays were examined to compare observed and imputed distributions on a common metric. Standardization facilitates direct comparison across variables and provides an additional assessment of whether the imputation procedure preserved the relative location, spread, and shape of the original data distributions.

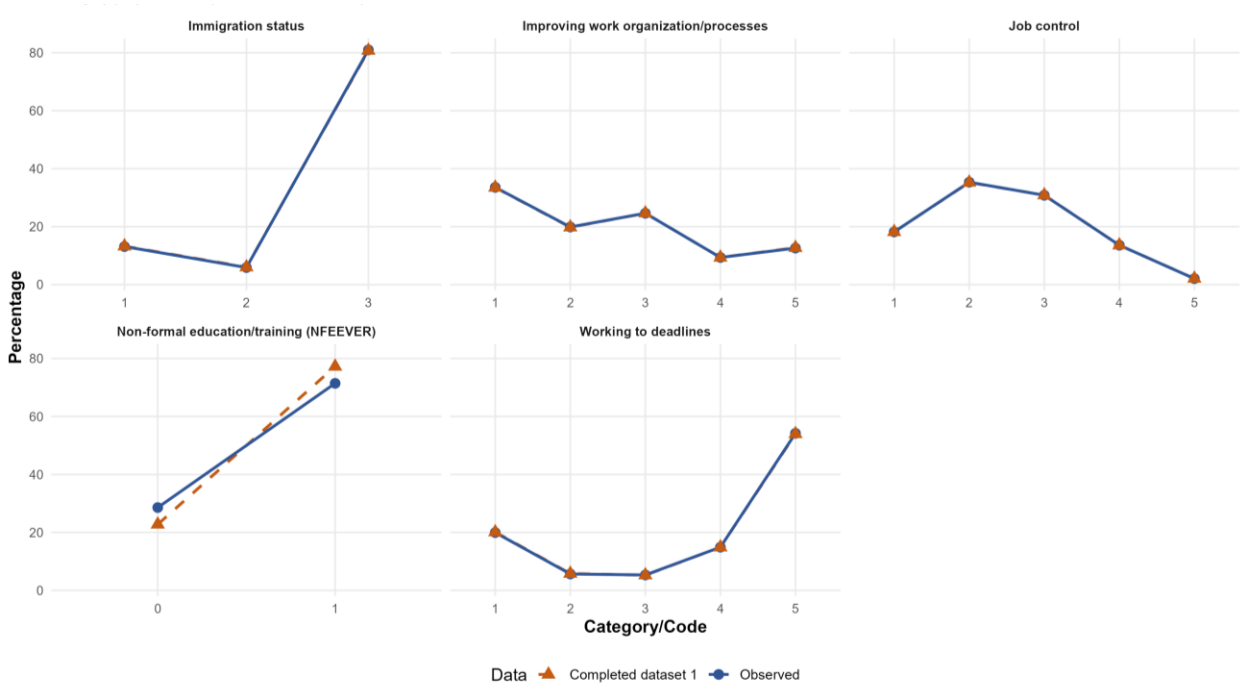
Figures 4-6A and 4-6B further examined whether the imputation procedure preserved the distributions of the study variables. Figure 4-6 A presents standardized density overlays for continuous and multi-level variables, showing substantial overlap between the observed data and completed dataset 1 and indicating generally preserved distributional shapes.

Figure 4-6 Standardized Overlay across Key Variables

A.



B.



Note.

The figure shows standardized distribution overlays for continuous and multi-level variables. Blue solid lines represent observed data; orange dashed lines represent completed dataset 1. Similar curves indicate preservation of the observed distribution. Figure 4-6A (from left 1-5) uses Density on the y-axis. It contains variables treated as continuous or multi-level for the distributional diagnostic. The density curves show the shape of the distribution after the variables were standardized. Density is not a percentage. Its purpose is to see whether the blue observed curve and orange completed-data curve have similar shapes. In your figure, they overlap very closely for most variables, with the most visible difference for ICT use at work. Figure 4-6 B (from bottom right 1-5) uses Percentage on the y-axis. These variables are discrete/categorical. A density curve is less informative for something such as NFEEVER, which has only categories 0 and 1. Instead, the graph compares the percentage of observations in each category before and after imputation. This is why NFEEVER, for example, shows roughly 29% versus 71% in the observed data and approximately 23% versus 77% in completed dataset 1.

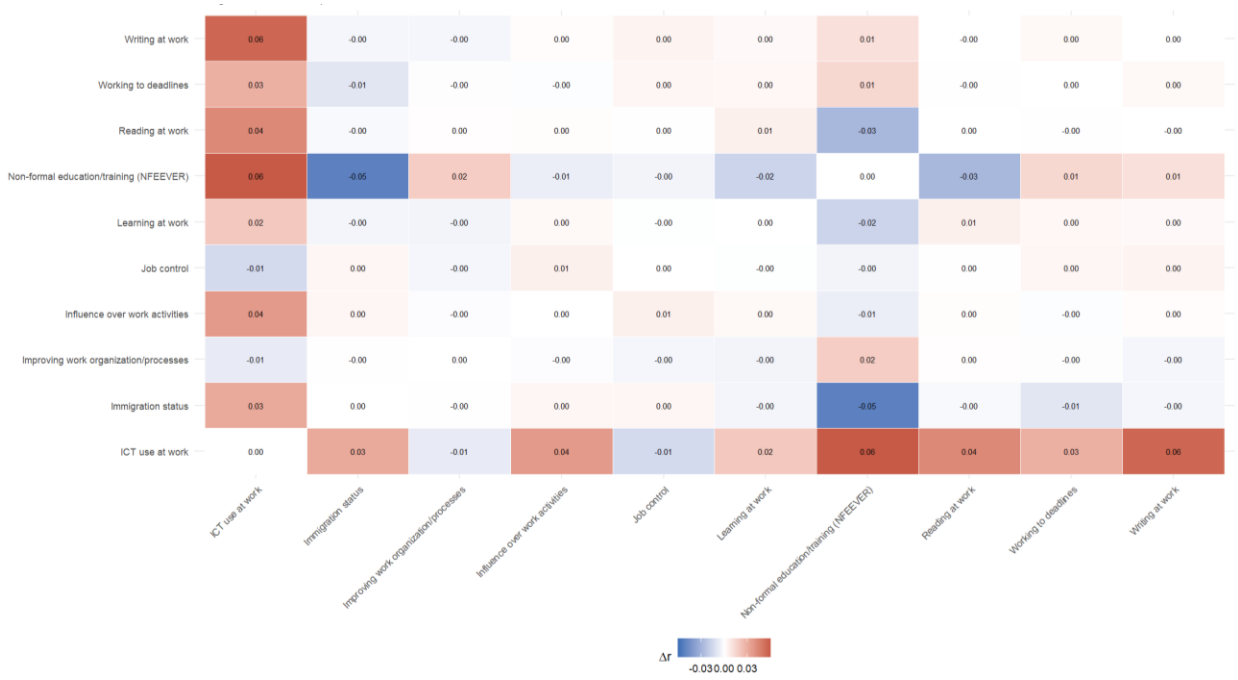
Figure 4-6 B compares category proportions for discrete variables and similarly shows close correspondence between the observed and completed distributions for most variables. NFEEVER showed the most noticeable shift in category proportions, consistent with its high initial missingness and the modest distributional shift identified in Figure 4-3. Overall, the results

indicate that the imputation procedure generally preserved the distributional characteristics of the study variables, while supporting more cautious interpretation of analyses involving NFEEVER.

Correlation Structure Preservation

Following the assessment of individual variable distributions, the correlation structure was evaluated to determine whether multiple imputation preserved the relationships among the study variables. Preserving these multivariate associations is particularly important because SEM relies on the covariance structure of the data to estimate structural relationships.

Figure 4-7 Correlation Structure Preservation (Δr)



Note.

The figure shows the change in correlation (completed dataset 1 minus observed data). Blue indicates a decrease in correlation, white indicates little or no change, and red-orange indicates an increase. Mean absolute change = 0.012; maximum absolute change = 0.060.

Figure 4-7 examines whether the correlation structure among the study variables was preserved following imputation. Each cell represents the change in correlation (Δr) between completed dataset 1 and the observed data, with values closer to zero indicating greater

preservation. The mean absolute change was 0.012, and the maximum absolute change was 0.060, indicating generally small changes in relationships among variables. Overall, the results suggest that the imputation procedure largely preserved the observed correlation structure, which is particularly important for the subsequent SEM analyses.

Sample Characteristics

The initial sample included 3,765 respondents. To align with the study's focus on work-based learning (WBL), the analytic sample was restricted to employed adults, yielding 2,627 respondents (69.8%). Further restriction on individuals with valid WBL measures resulted in a model-eligible sample of 2,606 respondents (69.2%). To address missing data and avoid case-wise deletion, multiple imputations were applied, producing a final analytic dataset of 2,606 respondents (Table 4-1).

Table 4-1 Sample Structure

Stage of Sample Selection	Number of Respondents (N)	Percentage (%)
Original sample	3,765	100.0
Employed adults	2,627	69.8
Model-eligible (WBL present)	2,606	69.2
Imputation-ready dataset	2,606	69.2
Final analytic sample (post-imputation)	2,606	69.2

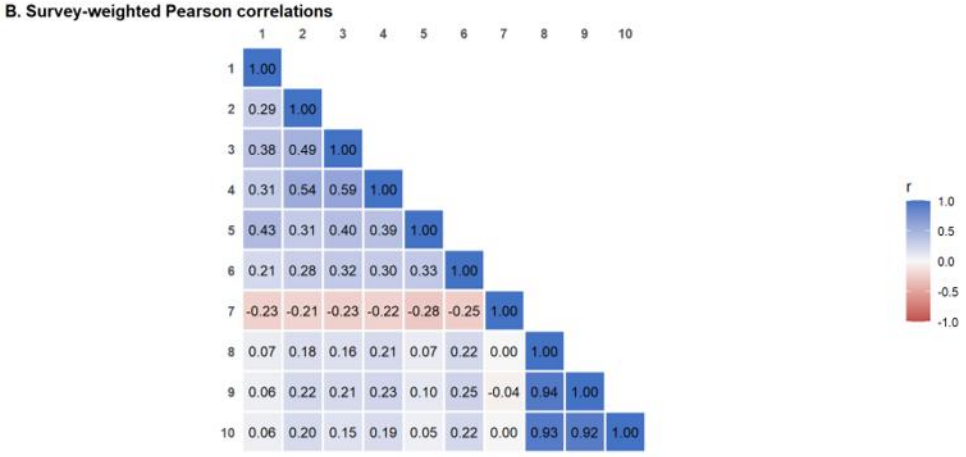
Weighted Descriptive Statistics and Correlations

Figure 4-8 presents the weighted descriptive statistics and correlation structure of the principal study variables. Overall, the workplace learning indicators exhibited moderate levels of engagement, while the standardized adult cognitive development measures (literacy, numeracy, and adaptive problem solving) were centered near zero, as expected after standardization. The correlation matrix indicates generally weak to moderate associations among the workplace learning variables and strong positive correlations among the three cognitive domains. These

patterns provide preliminary evidence supporting the distinct, yet related nature of the study constructs and establish a sound basis for the subsequent structural equation modeling and SEM-informed static policy optimization analyses.

Figure 4-8 Descriptive Statistics and Correlation Structure of the Main Study Variables

No	Variable	M	SD	Min	Max	Skew	Kurt
1	Learning at work	2.265	0.938	-0.534	3.656	-0.630	0.704
2	ICT use at work	2.058	1.117	0.297	4.472	0.542	-0.426
3	Reading at work	2.183	1.067	-0.753	5.218	-0.029	1.488
4	Writing at work	2.106	1.016	0.208	3.634	-0.383	-0.446
5	Influence over work activities	2.327	1.098	0.031	4.993	0.213	0.228
6	Working to deadlines	3.745	1.602	1.000	5.000	-0.868	-0.952
7	Reflection: improving work organization	2.477	1.376	1.000	5.000	0.504	-0.924
8	Literacy	-0.013	1.019	-3.266	2.282	-0.721	0.388
9	Numeracy	0.003	1.014	-3.913	2.606	-0.587	0.382
10	Adaptive problem solving	0.003	1.002	-3.731	2.533	-0.563	0.284



Note.

M and SD are calculated using PIAAC final sampling weight (SPFWT0). Pearson correlations are also weighted using SPFWT0. Minimum, maximum, skewness, and kurtosis describe the analytic values. Literacy, numeracy, and adaptive problem solving are standardized scores.

Comparison with full PIAAC sample to assess representativeness

Figure 4-9 compares the weighted distributions of key demographic and employment characteristics across the full U.S. PIAAC 2023 sample, the eligible employed sample, and the final analytical sample. The distributions were highly comparable across the three samples, indicating that restricting the analysis to employed adults and applying multiple imputation did

not materially alter the composition of the study population. For example, females represented approximately 53% of the full sample, 49% of the eligible employed sample, and 50% of the final analytical sample, while males accounted for the remaining 47–50%. Educational attainment also remained stable, with respondents holding some college or postsecondary education (ISCED 5–6) comprising approximately 42–45% of all three samples, and those with graduate education (ISCED 7–8) representing about 18–20%. Occupational and employment-sector distributions showed similarly small differences, with professional occupations remaining the largest occupational group and the service, industry, and public administration sectors consistently accounting for substantial proportions of respondents. Overall, these findings suggest that the analytical sample closely represents the eligible employed U.S. adult population and supports the generalizability of the subsequent SEM and SEM-informed static policy optimization analyses.

Figure 4-9 Comparison of the Analytical Sample with the Full U.S. PIAAC 2023 Sample



Note.

The figure is a weighted comparison of the full, eligible employed, and final analytic samples, showing distribution by gender, education, occupation, and sector. For occupation and sector, the 12 most prevalent categories are displayed.

These findings support the representativeness of the final analytical sample and provide confidence that the subsequent SEM and SEM-informed static policy optimization analyses are based on a sample that closely reflects the characteristics of the eligible employed U.S. adult population.

Reliability of Workplace Learning

The reliability of the Workplace Learning (WBL) construct was evaluated to determine the internal consistency of both the full and refined measurement models. Reliability was assessed using Cronbach's alpha, McDonald's omega, and the average inter-item correlation. The results are summarized in Figure 4-10 and Table 4-2.

Internal consistency

Figure 4-10 Summary of Reliability and Convergent Validity of WBL Measurements

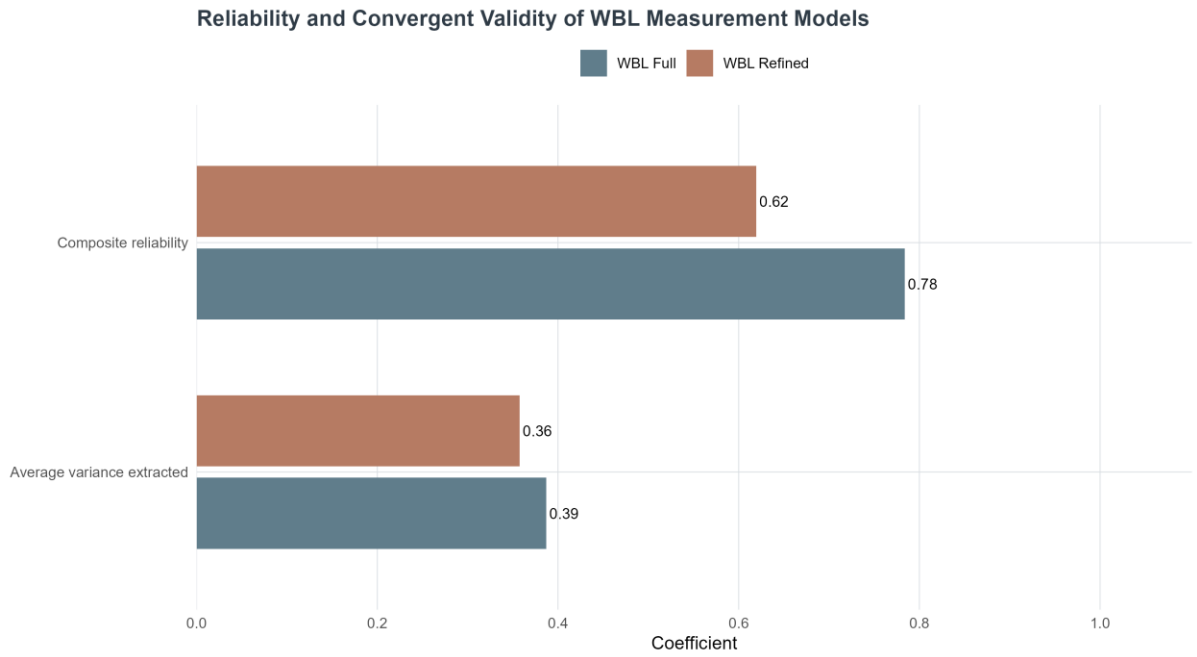


Figure 4-10 summarizes the reliability and construct validity of the full and refined Workplace Learning (WBL) measures. The full WBL measure demonstrated satisfactory internal consistency, with a standardized Cronbach's alpha of 0.780, McDonald's omega of 0.786, and an average inter-item correlation of 0.372. The refined WBL measure exhibited lower but acceptable reliability, with a standardized Cronbach's alpha of 0.601, McDonald's omega of 0.608, and an average inter-item correlation of 0.335. Composite reliability was 0.784 for the full model and 0.619 for the refined model, while the Average Variance Extracted (AVE) was 0.387 and 0.358, respectively. Overall, the full WBL measure demonstrated stronger psychometric properties, whereas the refined measure retained acceptable reliability and construct validity while providing a more parsimonious representation of workplace learning.

Table 4-2 Reliability and Construct Validity of the Workplace Learning Measure

Measure	WBL Full	WBL Refined
Number of indicators	6	3
Standardized Cronbach's α	0.780	0.601
McDonald's ω	0.786	0.608
Composite Reliability (CR)	0.784	0.619
Average Variance Extracted (AVE)	0.387	0.358
Mean standardized loading	0.609	0.590
Range of standardized loadings	0.435–0.763	0.460–0.683
Average inter-item correlation	0.372	0.335

Note.

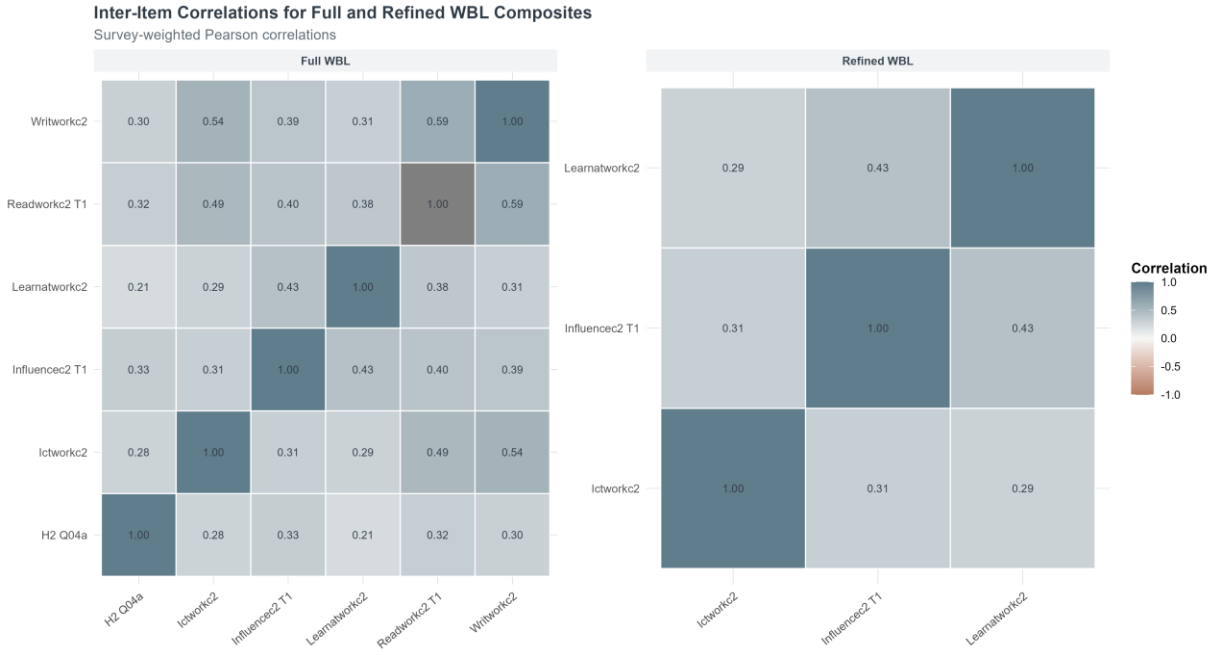
Cronbach's α = standardized Cronbach's alpha; ω = McDonald's omega; CR = Composite Reliability; AVE = Average Variance Extracted. The refined WBL measure retained acceptable reliability while providing a more parsimonious representation of the workplace learning construct.

Inter-item correlations and item retention decisions

Figure 4-11 presents the inter-item correlation matrices for the full and refined WBL measures. The retained indicators exhibited generally moderate positive correlations, indicating that they captured related but distinct aspects of workplace learning. The refined measure showed a more

coherent correlation structure with reduced redundancy among indicators, supporting its use in the subsequent SEM analyses.

Figure 4-11 Inter-item correlation for WBL- Full and WBL-Refined Composites

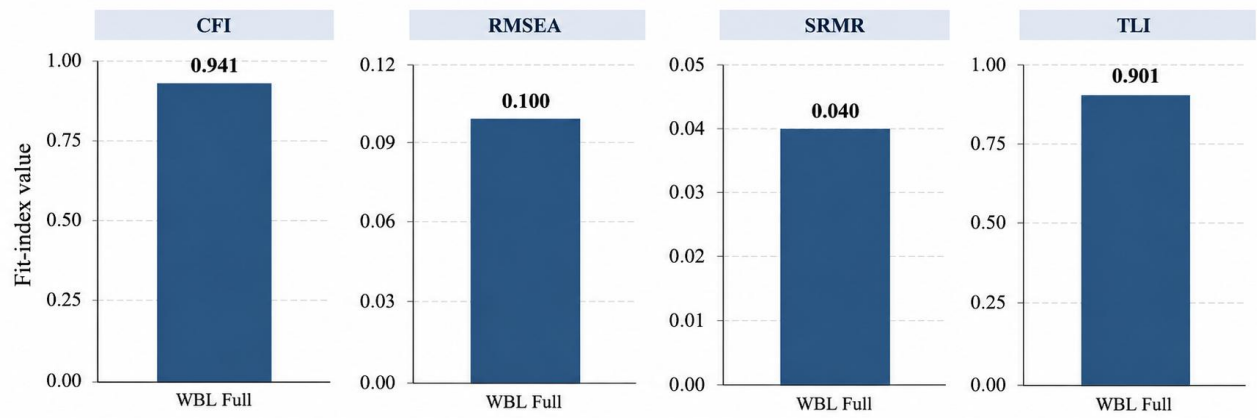


Construct Validity

Confirmatory factor analysis results

Figure 4-12 compares the overall fit of the full and refined CFA models. The refined measurement model demonstrated improved overall model fit across the principal fit indices, including CFI, TLI, RMSEA, and SRMR, indicating that the refined specification provided a better representation of the underlying workplace learning construct.

Figure 4-12 Summary of Fit Indices – Need to be developed for WBL-Full and WBL-Refined



Model	CFI	RMSEA	SRMR	TLI
WBL Full (6 indicators)	0.941	0.100	0.040	0.901

Note.

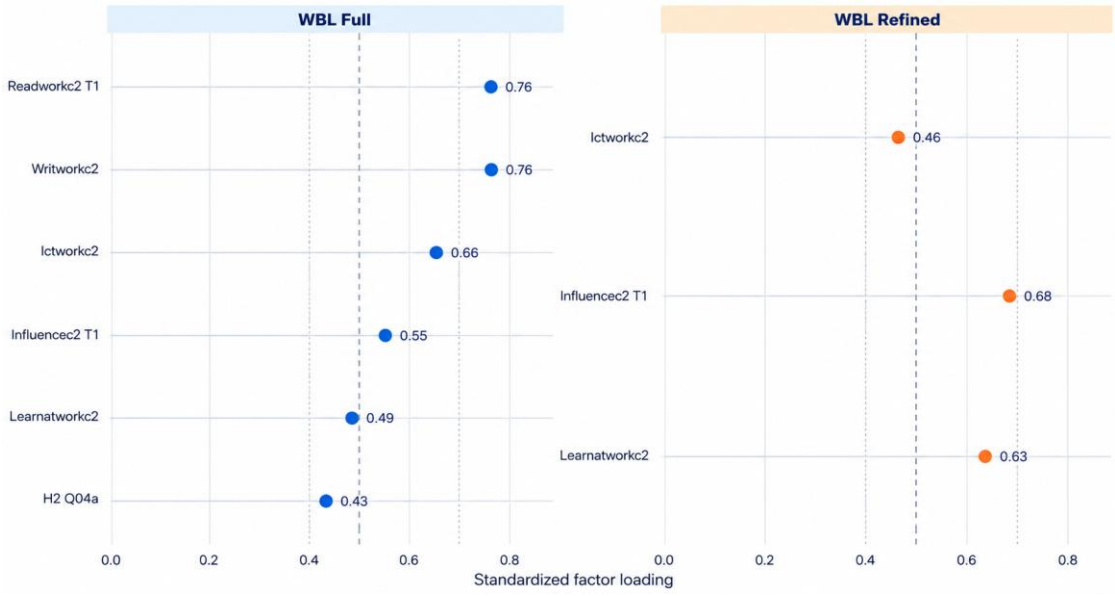
One -factor CFA estimated using MLR with FIML and PIAAC main sampling weight.

Recommended thresholds: CFI ≥ 0.90 (good ≥ 0.95); RMSEA ≤ 0.08 (good ≤ 0.06); SRMR ≤ (good ≤ 0.05); TLI ≥ 0.90. Abbreviations: CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; TLI = Tucker – Lewis Index.

Standardized loadings and construct validity

Figure 4-13 presents the standardized factor loadings for the full and refined Workplace Learning (WBL) measurement models.

Figure 4-13 Standardized CFA Loadings for Full and Refined WBL Measures



Note.

The figure shows standardized CFA loadings for full and refined WBL measures. One-factor measurement models were estimated using MLR, FIML, and the PIAAC main sampling weight. Reference lines at 0.40, 0.50, and 0.70 are descriptive guides and are not treated as strict cutoff criteria.

For the full WBL model, standardized loadings ranged from 0.43 (Improving work organization) to 0.76 (Reading at work and Writing at work), with ICT use at work (0.66), Influence over work activities (0.55), and Learning at work (0.49) demonstrating moderate loadings. In the refined WBL model, the retained indicators exhibited standardized loadings of 0.63 for Learning at work, 0.68 for Influence over work activities, and 0.46 for ICT use at work. Overall, the refined model retained the strongest and most theoretically relevant indicators while maintaining adequate factor loadings, supporting its use as a parsimonious measure of workplace learning in the subsequent SEM analyses.

Composite Reliability and AVE

The construct validity statistics for the full and refined WBL measures. Composite reliability values indicated satisfactory construct reliability, while the Average Variance Extracted (AVE) supported adequate convergent validity. Together with the reliability and CFA results, these findings provide evidence that the refined WBL measure demonstrates acceptable psychometric properties for the subsequent structural equation modeling analyses.

Although the refined WBL measure demonstrated acceptable psychometric properties, the six-item full WBL measure was retained as the primary operationalization for the SEM and subsequent static policy optimization. This decision was based on both theoretical and empirical considerations. The full measure captured a broader range of workplace-learning affordances, including learning at work, ICT use, reading, writing, influence over work activities, and on-the-job learning, thereby providing greater content coverage of the WBL construct. Empirically, the full measure also demonstrated stronger internal consistency than the refined measure, with a

standardized Cronbach's alpha of .780 compared with .601 for the refined measure and a higher average inter-item correlation (.372 vs. .335). The refined measure was therefore retained as an alternative measurement specification and sensitivity check rather than replacing the broader WBL construct. This approach allowed the study to preserve theoretical breadth in the primary analyses while evaluating whether conclusions were sensitive to a more parsimonious WBL specification.

Summary of Data Characteristics

Overall, the analytic sample demonstrated high data quality suitable for subsequent structural equation modeling and SEM-informed static policy optimization. Multiple imputation successfully addressed missing data while preserving the original variable distributions, standardized values, and correlation structure. The analytic sample remained broadly representative of the employed U.S. adult population included in PIAAC 2023. Reliability analyses indicated good internal consistency for both the full and refined WBL measures, while CFA results supported acceptable measurement properties and construct validity. Collectively, these findings provide confidence that the data satisfy the assumptions required for the structural and policy analyses presented in the following sections.

Structural Model: Reciprocal WBL-ACD Relationships (RQ 1)

Model comparison across literacy, numeracy, and APS

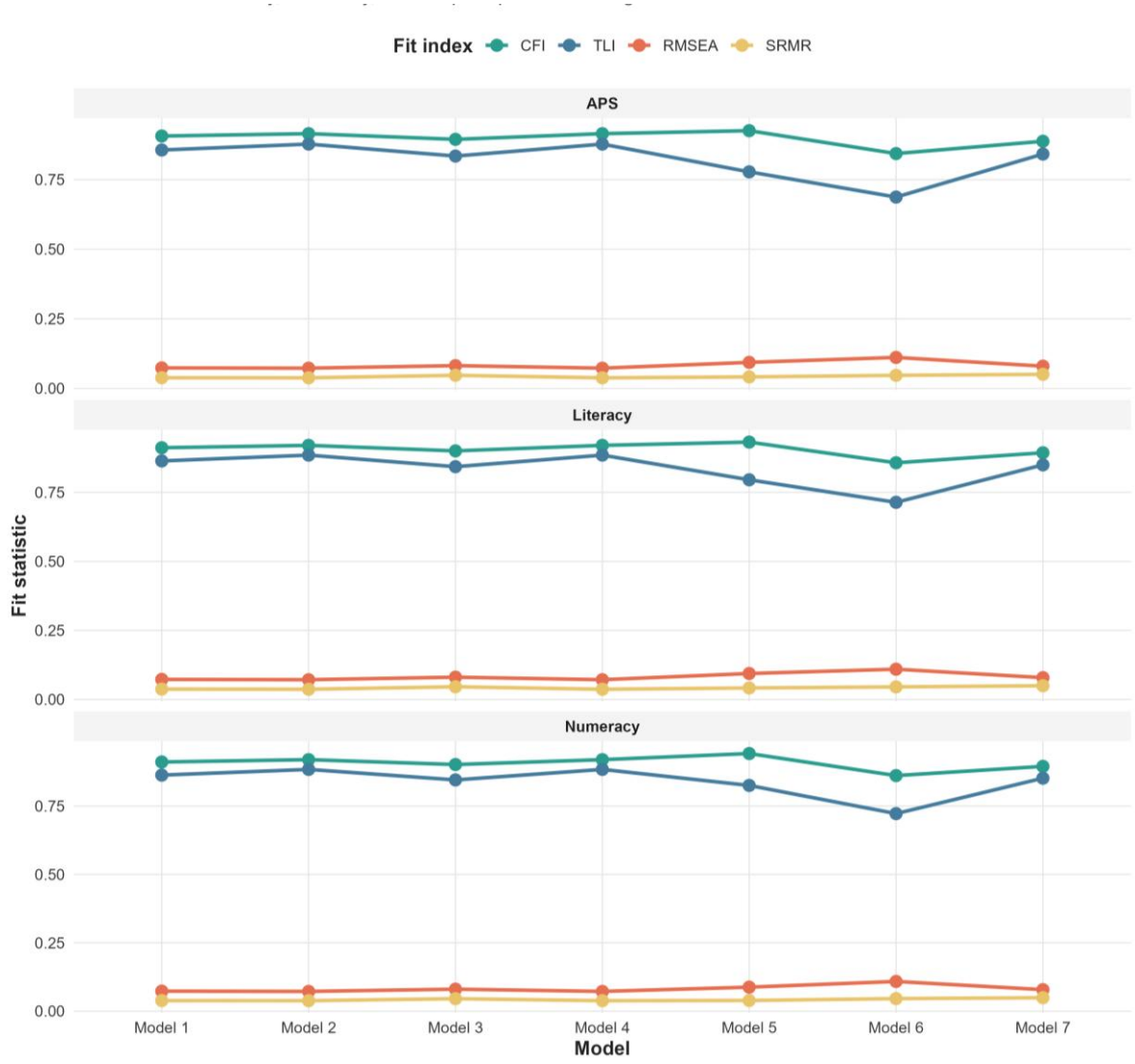
Research Question 1 examined the nature of the reciprocal association between WBL and ACD. The first step in addressing this question was to compare the ordered SEM families across literacy, numeracy, and adaptive problem solving (APS). A consistent pattern emerged across the three cognitive domains, with the Reverse SEM (Model 2) and Correlated Disturbance SEM

(Model 4) demonstrating the strongest overall fit when CFI, RMSEA, and SRMR were considered jointly (Figure 4.14; Table 4-3).

For literacy, Model 2 achieved the strongest average ranking (1.33), with CFI = .920, RMSEA = .072, and SRMR = .037. Model 4 showed the same fit indices when rounded to three decimal places (CFI = .920, RMSEA = .072, SRMR = .037) and ranked second (average rank = 2.33). Model 1, the Forward Recursive Mediation SEM, ranked third (average rank = 3.33), with slightly lower CFI (.911) and slightly higher RMSEA (.073) and SRMR (.038).

The pattern was highly similar for numeracy, although the ordering of the two leading models was reversed. Model 4 ranked first (average rank = 1.33), and Model 2 ranked second (2.33); both produced CFI = .919, RMSEA = .072, and SRMR = .038 when rounded to three decimal places. Model 1 again ranked third (3.33), with CFI = .911, RMSEA = .073, and SRMR = .039. Results for APS were similarly consistent. Model 4 ranked first (average rank = 1.67), followed closely by Model 2 (2.00). Both models yielded CFI = .915, RMSEA = .073, and SRMR = .038 when rounded to three decimal places. Model 1 again ranked third (3.33), with CFI = .907, RMSEA = .074, and SRMR = .039. Thus, Model 1 maintained the same relative position across all three domains, whereas Models 2 and 4 alternated between the first and second positions.

Figure 4-14 Comparative Model-fit profile across literacy, numeracy, and APS.



Note.

CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; APS = adaptive problem solving. Higher CFI and TLI values and lower RMSEA and SRMR values indicate comparatively better model fit. The figure displays fit statistics for Models 1–7 across literacy, numeracy, and APS to illustrate the comparative fit profile of each specification. Model comparison was based on the joint pattern of fit indices rather than any single fit statistic. TLI is displayed as an additional descriptive fit index but was not included in the average-rank calculation reported in Table 4-3.

Table 4-3 Comparative performance of the best-fitting SEM specifications across cognitive domains

Domain	Model	CFI	RMSEA	SRMR	Average rank
Literacy	Model 2: Reverse SEM	0.920	0.072	0.037	1.33
	Model 4: Correlated Disturbance SEM	0.920	0.072	0.037	2.33
	Model 1: Forward Recursive Mediation SEM	0.911	0.073	0.038	3.33
Numeracy	Model 4: Correlated Disturbance SEM	0.919	0.072	0.038	1.33
	Model 2: Reverse SEM	0.919	0.072	0.038	2.33
	Model 1: Forward Recursive Mediation SEM	0.911	0.073	0.039	3.33
APS	Model 4: Correlated Disturbance SEM	0.915	0.073	0.038	1.67
	Model 2: Reverse SEM	0.915	0.073	0.038	2.00
	Model 1: Forward Recursive Mediation SEM	0.907	0.074	0.039	3.33

Note.

CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. Average rank reflects the joint ranking of models across CFI, RMSEA, and SRMR, with lower values indicating stronger overall relative performance. Fit statistics are displayed to three decimal places; therefore, models with identical displayed values may differ slightly in the underlying unrounded estimates used to calculate ranks.

Figure 4.14 further demonstrates that performance on individual fit indices did not always correspond to the strongest overall fit profile. Some alternative specifications achieved comparatively high CFI values while simultaneously showing less favorable RMSEA, SRMR, or TLI values. Therefore, model comparison was based on the joint pattern of fit statistics rather than on any single index. Across the three domains, Models 2 and 4 consistently provided the most balanced fit profiles, while Model 1 remained a stable third-ranked specification.

Collectively, the similarity of the fit patterns across literacy, numeracy, and APS indicates that the comparative performance of the SEM specifications was consistent across cognitive domains. However, model fit alone does not establish whether the WBL-ACD association is predominantly forward, reverse, or reciprocal. The structural path estimates

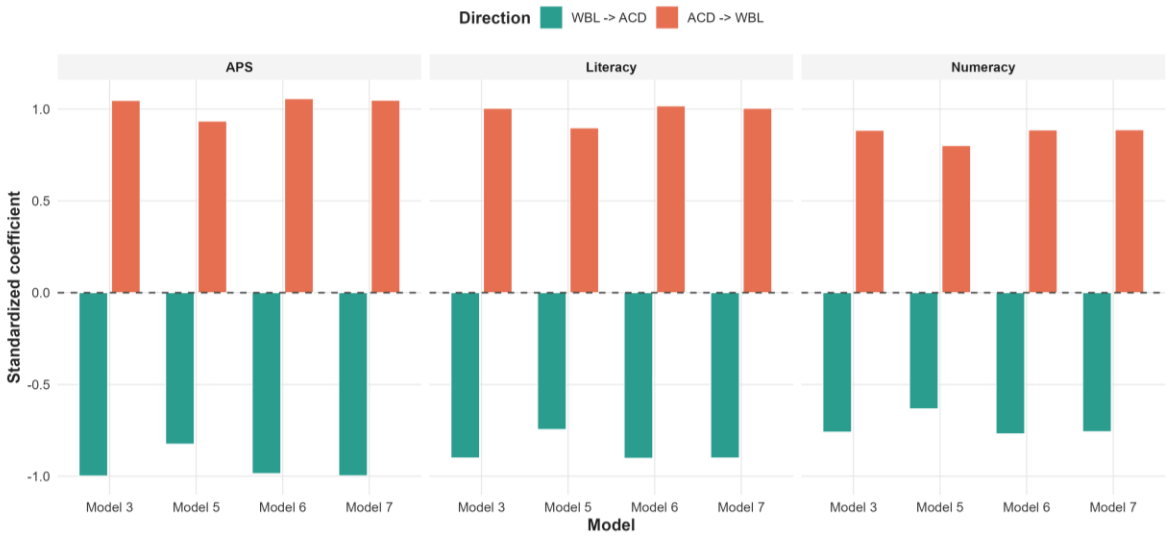
presented in the following section were therefore examined to determine the direction, magnitude, and statistical significance of the estimated WBL-ACD associations.

Reciprocal path estimates and directionality patterns

The reciprocal structural associations between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) were examined across four simultaneous SEM specifications: Models 3, 5, 6, and 7. Figure 4-15 illustrates the magnitude and direction of the standardized WBL → ACD and ACD → WBL coefficients across literacy, numeracy, and adaptive problem solving (A PS), while Table 4-4 presents the corresponding numerical path estimates and statistical significance levels. Together, these results provide a comparative assessment of the directionality patterns underlying the proposed WBL–ACD nexus.

The second stage of addressing Research Question 1 examined the direction and magnitude of the structural associations between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). Four simultaneous reciprocal specifications were compared: Reciprocal Latent SEM (Model 3), Reciprocal Observed-WBL SEM (Model 5), Reciprocal Refined Latent-WBL SEM (Model 6), and Identified Reciprocal SEM (Model 7). The analysis considered both WBL → ACD and ACD → WBL paths across literacy, numeracy, and adaptive problem solving (APS).

Figure 4-15 Standardized directional path coefficients from reciprocal SEM specifications across literacy, numeracy, and adaptive problem solving.



Across all three cognitive domains, the four reciprocal specifications exhibited a consistent pattern of negative WBL → ACD coefficients and positive ACD → WBL coefficients. All 24 reported reciprocal path coefficients were statistically significant at the nominal $p < .001$ level. However, their magnitudes differed across model specifications and cognitive domains.

For literacy, the standardized WBL → ACD coefficients ranged from −0.902 to −0.745, whereas the ACD → WBL coefficients ranged from 0.898 to 1.017. Model 3 produced a negative WBL → ACD coefficient ($\beta = -0.900$) and a positive ACD → WBL coefficient ($\beta = 1.004$). Model 5 yielded comparatively smaller absolute coefficients ($\beta = -0.745$ and $\beta = 0.898$, respectively), suggesting that the estimated associations were sensitive to whether WBL was represented as a latent construct or an observed composite. Model 6 produced coefficients of −0.902 and 1.017, while Model 7 closely reproduced the Model 3 estimates (−0.900 and 1.004).

Table 4-4 Standardized reciprocal path estimates across literacy, numeracy, and adaptive problem solving

Domain	SEM Specification	WBL → ACD (Std.)	WBL → ACD Significance	ACD → WBL (Std.)	ACD → WBL Significance
Literacy	Model 3: Reciprocal Latent SEM	-0.900	***	1.004	***
	Model 5: Reciprocal Observed WBL	-0.745	***	0.898	***
	Model 6: Reciprocal Refined Latent WBL	-0.902	***	1.017	***
	Model 7: Identified Reciprocal SEM	-0.900	***	1.004	***
Numeracy	Model 3: Reciprocal Latent SEM	-0.759	***	0.884	***
	Model 5: Reciprocal Observed WBL	-0.632	***	0.801	***
	Model 6: Reciprocal Refined Latent WBL	-0.769	***	0.886	***
	Model 7: Identified Reciprocal SEM	-0.757	***	0.887	***
Adaptive Problem Solving	Model 3: Reciprocal Latent SEM	-0.998	***	1.047	***
	Model 5: Reciprocal Observed WBL	-0.825	***	0.934	***
	Model 6: Reciprocal Refined Latent WBL	-0.985	***	1.057	***
	Model 7: Identified Reciprocal SEM	-0.997	***	1.048	***

Note.

1. Standardized coefficients are reported for the reciprocal SEM specifications (Models 3, 5, 6, and 7). Statistical significance is denoted as *** $p < .001$. These coefficients are extracted from the bidirectional structural path estimates generated by the reciprocal SEM models.

2. Values represent fully standardized structural path coefficients. Statistical significance reflects nominal model-based tests. Coefficients approaching or exceeding an absolute value of 1.00 should be interpreted cautiously in light of the estimation diagnostics discussed in the text.

For numeracy, the WBL → ACD coefficients ranged from −0.769 to −0.632, and the ACD → WBL coefficients ranged from 0.801 to 0.887. Model 3 yielded coefficients of −0.759 and 0.884, respectively. Model 5 again produced smaller absolute estimates (−0.632 and 0.801), while Model 6 yielded −0.769 and 0.886. Model 7 produced similar coefficients of −0.757 and 0.887. Compared with literacy and APS, numeracy generally exhibited smaller absolute reciprocal coefficients.

For APS, the WBL → ACD coefficients ranged from −0.998 to −0.825, while the ACD → WBL coefficients ranged from 0.934 to 1.057. Model 3 yielded coefficients of −0.998 and 1.047, respectively. Model 5 produced comparatively smaller estimates (−0.825 and 0.934), whereas Model 6 yielded −0.985 and 1.057. Model 7 again closely reproduced the Model 3 estimates (−0.997 and 1.048). The APS results exhibited particularly large, standardized coefficients, several approaching or exceeding an absolute value of 1.00.

The consistently opposing signs of the reciprocal coefficients are important for interpreting the proposed WBL–ACD nexus. Within these simultaneous specifications, higher cognitive proficiency was associated with greater WBL engagement, conditional on the modeled reciprocal system, whereas the estimated WBL → ACD path was negative. This pattern does not support the hypothesized positive reinforcement in both directions. However, because the reciprocal estimates were unusually large and accompanied by estimation warnings, the negative WBL → ACD coefficients should not be interpreted as evidence that workplace learning reduces cognitive proficiency (Bollen, 1989; Nagase & Kano, 2017; Wong & Law, 1999).

Comparison with alternative specifications further illustrates the model dependence of the estimated relationships. The Forward Recursive Mediation SEM (Model 1) produced small positive standardized WBL → ACD coefficients for literacy ($\beta = 0.068$, $p = .029$), numeracy (β

= 0.076, p = .012), and APS (β = 0.061, p = .038). In contrast, the Reverse SEM (Model 2) produced small positive ACD → WBL coefficients for literacy (β = 0.049, p = .112), numeracy (β = 0.069, p = .021), and APS (β = 0.037, p = .188), with only the numeracy coefficient reaching the nominal .05 significance level.

The two-stage least-squares robustness specification (Model 8) provided additional evidence of this directional difference. The unstandardized WBL → ACD coefficients were positive but not statistically significant for literacy (b = 0.024, p = .454), numeracy (b = 0.017, p = .576), or APS (b = 0.042, p = .168). Conversely, the ACD → WBL coefficients were positive and statistically significant for literacy (b = 0.376, p < .001), numeracy (b = 0.340, p < .001), and APS (b = 0.411, p < .001). Because Model 8 reports unstandardized coefficients and relies on instrumental-variable assumptions, these magnitudes are not directly comparable with the standardized SEM estimates. The interpretation of these 2SLS estimates remains conditional on the relevance and validity of the specified instrumental variables, particularly the exclusion restrictions underlying the simultaneous equations (Bollen, 1989).

Taken together, the structural path estimates reveal a clear dependence on model specification. The forward model yielded small positive WBL → ACD associations, the reverse model yielded small positive ACD → WBL associations, and the simultaneous reciprocal specifications yielded large coefficients with opposing signs. The 2SLS results provided additional support for a positive ACD → WBL association under its identifying assumptions, while offering less evidence for a WBL → ACD association. These differences indicate that the nature of the WBL–ACD relationship cannot be established from the simultaneous reciprocal coefficients alone.

Diagnostics and numerical stability

The interpretation of the structural path estimates requires consideration of model convergence, estimation warnings, coefficient magnitude, and sensitivity across plausible values and imputed datasets. These diagnostics are particularly important for simultaneous reciprocal SEM specifications, where identification problems and numerical instability may affect the reliability of estimated parameters.

All 21 SEM specifications converged across the three cognitive domains, representing seven models estimated separately for literacy, numeracy, and APS. However, all 21 specifications generated warnings indicating that the estimated parameter variance-covariance matrix was not positive definite. These warnings suggest potential identification or numerical estimation problems and limit confidence in the reported standard errors and statistical significance tests. Thus, convergence alone was insufficient to establish that the models produced statistically reliable parameter estimates.

The reciprocal specifications also exhibited unusually large standardized structural coefficients. For literacy, the ACD → WBL coefficients exceeded 1.00 in Models 3 ($\beta = 1.004$), 6 ($\beta = 1.017$), and 7 ($\beta = 1.004$). For APS, the corresponding coefficients were 1.047, 1.057, and 1.048. The negative WBL → ACD coefficients were also particularly large in APS, ranging from −0.998 to −0.825. Although standardized regression coefficients can exceed an absolute value of 1.00 in certain simultaneous-equation models, these estimates warrant additional scrutiny when accompanied by warnings about the parameter covariance matrix.

Supplemental sensitivity analyses were conducted for Models 3 and 7 across five multiply imputed datasets and ten plausible values per cognitive domain, yielding 50 estimation runs for each model-domain combination. For Model 3, the mean standardized WBL → ACD

coefficients were −0.978 for literacy, −0.813 for numeracy, and −1.080 for APS. The corresponding mean ACD → WBL coefficients were 1.055, 0.914, and 1.098, respectively. Model 7 produced nearly identical mean standardized coefficients: −0.979, −0.811, and −1.079 for WBL → ACD, and 1.054, 0.917, and 1.099 for ACD → WBL.

The reported sign-consistency measure was 1.00 for every model-domain-direction combination, indicating that all 50 runs retained the same directional sign. This consistency suggests that the opposing coefficient signs were not unique to a single plausible value or completed imputation dataset. Nevertheless, several mean standardized coefficients remained close to or exceeded an absolute value of 1.00, particularly for literacy and APS. Therefore, the sensitivity results establish consistency of the estimated signs across the examined datasets but do not resolve the underlying identification concerns.

The comparison between Models 3 and 7 provides an additional qualification. Their nearly identical estimates suggest that the differences in their specified covariance structures did not materially change the reciprocal path estimates. However, this similarity should not be interpreted as independent confirmation of the reciprocal relationships because the two models share closely related structural equations and identifying assumptions.

Overall, the diagnostics indicate that the simultaneous reciprocal specifications produced consistent directional signs but exhibited unresolved numerical and identification concerns. Consequently, their coefficient magnitudes and nominal significance levels require cautious interpretation. The results are retained as evidence of how the estimated WBL–ACD associations behave under competing simultaneous specifications, rather than as definitive estimates of a stable reciprocal process.

Synthesis: Nature of the WBL-ACD Association

The combined evidence from model-fit comparisons, structural path estimates, and numerical sensitivity analyses indicates that the observed relationship between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) is directionally asymmetric and dependent on model specification. Although the study proposed a symbiotic WBL–ACD nexus characterized by positive reinforcement in both directions, the empirical results did not establish such a relationship.

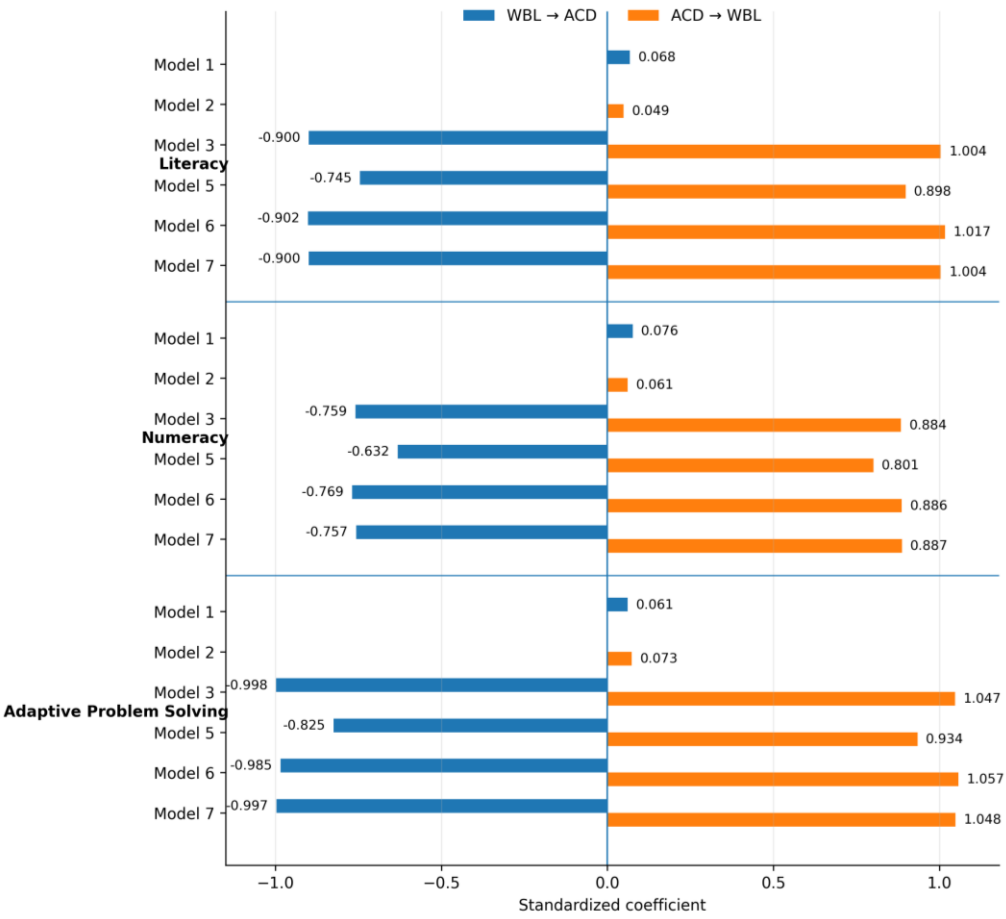
Three findings characterize the nature of the observed association. First, the forward recursive specifications produced small positive WBL → ACD coefficients across literacy ($\beta = 0.068$), numeracy ($\beta = 0.076$), and APS ($\beta = 0.061$), suggesting that workplace-learning engagement was positively associated with cognitive proficiency under these model assumptions. However, the corresponding 2SLS estimates were not statistically significant, indicating that the forward association was not consistently supported across estimation approaches.

Second, the ACD → WBL direction received comparatively stronger support in the instrumental-variable robustness specification, with positive coefficients for literacy ($b = 0.376$), numeracy ($b = 0.340$), and APS ($b = 0.411$), all statistically significant at the nominal $p < .001$ level. This pattern is consistent with the proposition that adults with stronger cognitive proficiency may be better positioned to engage with workplace-learning opportunities. Nevertheless, the reverse-only SEM yielded smaller coefficients, of which only numeracy was nominally statistically significant, and the instrumental-variable interpretation depends on the validity of its identification assumptions.

Third, the simultaneous reciprocal specifications consistently produced opposing directional coefficients, with negative WBL → ACD and positive ACD → WBL estimates. Although these signs were preserved across the reported sensitivity analyses, the unusually large standardized coefficients and estimation warnings limited the reliability of the reciprocal estimates. Consequently, the results do not establish a stable, mutually reinforcing relationship between WBL and ACD.

Taken together, the findings characterize the WBL–ACD relationship as a model-dependent association exhibiting directional asymmetry, with comparatively stronger evidence consistent with the ACD → WBL direction and less stable evidence for the WBL → ACD direction. This conclusion does not negate the theoretical possibility of reciprocal learning and cognitive development. Rather, it indicates that the proposed symbiotic nexus was not empirically established using the available cross-sectional data and modeling specifications. The findings therefore support a qualified interpretation of the WBL–ACD association while identifying the need for longitudinal and more strongly identified research to evaluate reciprocal reinforcement over time.

Figure 4-16 Comparison of standardized forward and reverse path coefficients across SEM specifications for literacy, numeracy, and adaptive problem solving.



Note.

Model 1 estimates only WBL-ACD; Model 2 estimates only ACD-WBL; and Models 3, 5, 6, and 7 estimate both directions.

Figure 4-16 compares the standardized forward and reverse path coefficients across the six SEM specifications for literacy, numeracy, and adaptive problem solving. Model 1 estimated only the forward pathway from work-based learning (WBL) to adult cognitive development (ACD), whereas Model 2 estimated only the reverse pathway from ACD to WBL. Models 3, 5, 6, and 7 simultaneously estimated both directional paths. Across all three cognitive domains, the forward and reverse recursive models (Models 1 and 2) produced relatively small positive standardized coefficients, indicating modest directional associations when estimated independently.

In contrast, the reciprocal SEMs generated substantially larger coefficients, with consistently negative WBL → ACD paths and positive ACD → WBL paths. The magnitude and direction of these reciprocal coefficients were highly consistent across literacy, numeracy, and adaptive problem solving, although the observed-WBL specification (Model 5) produced somewhat attenuated estimates relative to the latent-variable reciprocal models. Overall, the figure illustrates that the pattern of directional associations is remarkably stable across cognitive domains while also highlighting the differences between recursive and reciprocal SEM specifications. Because several reciprocal models exhibited estimation instability, these coefficients are interpreted as evidence of statistical interdependence between WBL and ACD rather than definitive estimates of stable simultaneous reciprocal effects.

Mediation Analysis

Table 4-5 Direct, indirect, and total effects of work-based learning on adult cognitive development (Model 1)

Cognitive Domain	Direct Effect (c′) (Std.)	Sig.	Indirect Effect (a × b) (Std.)	Sig.	Total Effect (Std.)	Sig.	Interpretation
Literacy	0.068	*	-0.023	*	0.045	n.s.	Partial mediation
Numeracy	0.076	*	-0.013	n.s.	0.062	*	Primarily direct effect
Adaptive Problem Solving	0.061	*	-0.025	*	0.036	n.s.	Partial mediation

Note.

Standardized coefficients are reported for mediation analysis. The indirect effect represents the pathway through involvement in improving work organization or work processes (h2_q14a_z). Total effects equal the sum of the direct and indirect effects. Significance codes: * p < .05.

The mediation analyses provide additional insight into the nature of the association between Work-Based Learning (WBL) and Adult Cognitive Development (ACD) by examining the indirect pathway through involvement in improving work organization or work processes.

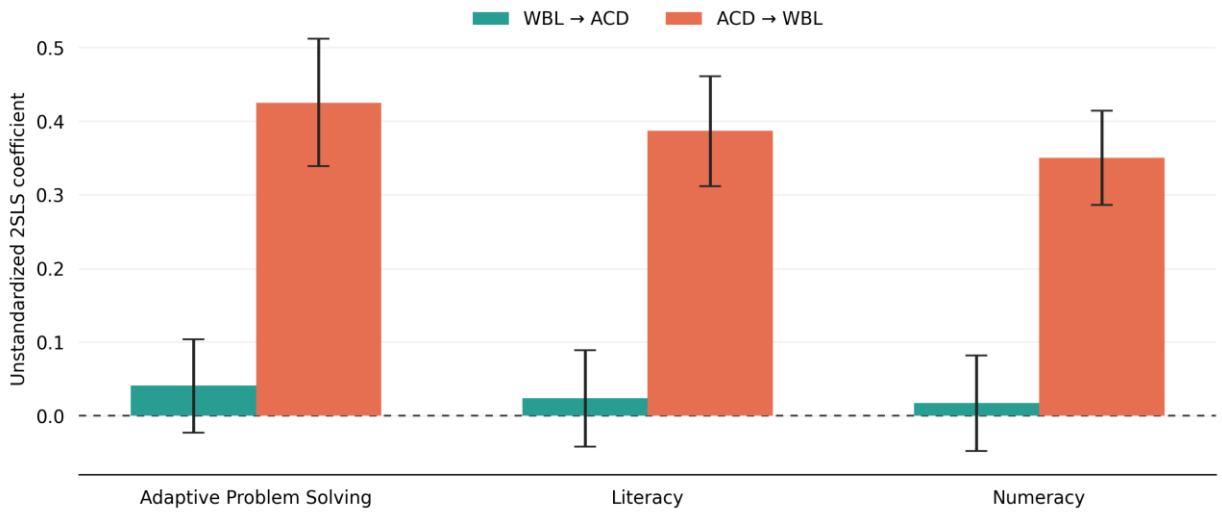
Across the three cognitive domains, the direct associations between WBL and ACD remained positive and statistically significant, with standardized coefficients of 0.068 for literacy, 0.076 for numeracy, and 0.061 for adaptive problem solving (APS). However, the estimated WBL → mediator path was negative ($\beta \approx -0.379$, $p < .001$), while the mediator → ACD paths were positive, producing negative indirect associations across all three domains. The indirect coefficients were statistically significant for literacy ($\beta = -0.023$) and APS ($\beta = -0.025$), but not for numeracy ($\beta = -0.013$). Consequently, the positive direct associations were partially offset by the opposing indirect associations for literacy and APS, resulting in smaller, statistically nonsignificant total effects ($\beta = 0.045$ and $\beta = 0.036$, respectively). This pattern is consistent with competitive or inconsistent mediation, in which the direct and indirect pathways have opposing signs (MacKinnon et al., 2000; Zhao et al., 2010). For numeracy, the indirect association was not statistically significant, and the positive total association remained statistically significant ($\beta = 0.062$), suggesting that the observed association was predominantly direct within the specified model. Overall, these findings indicate that the forward WBL–ACD association differs across cognitive domains and modeled pathways. The mediation results characterize statistical relationships within the cross-sectional data and do not establish a causal mediating mechanism.

Robustness Analyses

Model 8, presented in Figure 4-17, provided an instrumental-variable robustness assessment of the directional associations between Work-Based Learning (WBL) and Adult Cognitive Development (ACD). Across adaptive problem solving (APS), literacy, and numeracy, the estimated ACD → WBL coefficients were positive and statistically significant ($b = 0.425$, 0.387, and 0.350, respectively; all $p < .001$). In contrast, the WBL → ACD coefficients were comparatively small and statistically nonsignificant ($b = 0.041$, 0.024, and 0.017, respectively),

with 95% confidence intervals that included zero. These findings suggest that the positive ACD → WBL association was more consistently supported across alternative specifications, whereas the magnitude, direction, and statistical significance of the WBL → ACD association varied across estimation approaches. Overall, the results provide additional evidence consistent with a model-dependent, directionally asymmetric WBL–ACD relationship. However, the interpretation of the 2SLS estimates remains conditional on the relevance and validity of the specified instrumental variables and does not establish causal direction.

Figure 4-17 Comparison of standardized forward and reverse path coefficients across SEM specifications for literacy, numeracy, and adaptive problem solving.



Note.

Bars represent unstandardized two-stage least-squares (2SLS) coefficients. Error bars indicate heteroskedasticity-robust 95% confidence intervals. WBL = Work-Based Learning; ACD = Adult Cognitive Development. All ACD → WBL estimates are statistically significant ($p < .001$), whereas WBL → ACD estimates are not statistically significant ($p > .05$).

Table 4-6 shows the two-stage least squares (2SLS) robustness analysis results. The two-stage least-squares (2SLS) robustness analysis provided additional evidence of directional asymmetry in the association between Work-Based Learning (WBL) and Adult Cognitive

Development (ACD). Across adaptive problem solving (APS), literacy, and numeracy, the estimated ACD → WBL coefficients were positive and statistically significant (b = 0.425, 95% CI [0.339, 0.512]; b = 0.387, 95% CI [0.312, 0.461]; and b = 0.350, 95% CI [0.286, 0.414], respectively; all p < .001). In contrast, the WBL → ACD coefficients were small and statistically nonsignificant for APS (b = 0.041, 95% CI [−0.023, 0.104]), literacy (b = 0.024, 95% CI [−0.042, 0.089]), and numeracy (b = 0.017, 95% CI [−0.048, 0.082]). The positive ACD → WBL associations therefore appeared more consistently supported within the 2SLS specification, whereas the forward WBL → ACD associations remained statistically uncertain. These findings are consistent with a model-dependent, directionally asymmetric relationship, although their interpretation depends on the validity of the instrumental-variable assumptions and does not establish causal direction.

Table 4-6 Model 8 (2SLS) robustness estimates pooled across plausible values

Domain	Direction	2SLS Estimate	95% Confidence Interval	*p*	Interpretation
Adaptive Problem Solving	ACD → WBL	0.425	[0.339, 0.512]	< .001	Significant positive association
Adaptive Problem Solving	WBL → ACD	0.041	[-0.023, 0.104]	> .05	Not statistically significant
Literacy	ACD → WBL	0.387	[0.312, 0.461]	< .001	Significant positive association
Literacy	WBL → ACD	0.024	[-0.042, 0.089]	> .05	Not statistically significant
Numeracy	ACD → WBL	0.350	[0.286, 0.414]	< .001	Significant positive association
Numeracy	WBL → ACD	0.017	[-0.048, 0.082]	> .05	Not statistically significant

Note.

Estimates are pooled across ten plausible values using Rubin's rules. Confidence intervals are heteroskedasticity-robust. Positive sign consistency values (1.0 for five of six estimates and 0.9 for Numeracy WBL → ACD) indicate that the estimated direction of the effect was highly stable across plausible values.

Collectively, the robustness analyses indicate that the principal findings are not dependent on a single estimation approach. Despite differences in model assumptions and estimation procedures, the positive association between adult cognitive development and work-based learning remained consistent across methods. The 2SLS results reinforce the conclusion that WBL and ACD are interconnected, while providing partial support for the bidirectional association identified across the SEM analyses.

Structural Model-Informed Static Policy Optimization Findings (RQ 2)

SEM-informed Static Policy Optimization Framework

Research Question 2 examined how different types and intensities of work-based learning (WBL) influence adult cognitive development (ACD) through a SEM-informed static policy optimization framework. Unlike traditional optimization approaches that estimate long-term sequential learning policies, the present framework evaluated the expected cognitive outcomes associated with alternative workplace-learning strategies within empirically observed cognitive states. State-specific rewards were estimated from observed ACD outcomes and scaled using the standardized WBL → ACD path coefficient obtained from the Forward Recursive Mediation SEM (Model 1), thereby linking the optimization directly to the structural relationships identified in Research Question 1.

The optimization considered five candidate workplace-learning strategies: (1) no additional workplace-learning support, (2) training-oriented learning, (3) digital learning, (4) collaborative workplace learning, and (5) blended workplace learning. Individuals were classified into discrete cognitive states based on tertiles of work-based learning engagement and adult cognitive development, and the expected reward associated with each candidate action was

estimated for every state. The optimal static policy was defined as the workplace-learning strategy associated with the highest expected cognitive outcome within each state.

The results are presented in four stages. First, comparative action effects evaluate the overall performance of the candidate workplace-learning strategies across literacy, numeracy, and adaptive problem solving. Second, state-action reward estimates illustrate how expected cognitive outcomes vary across cognitive states and workplace-learning strategies. Third, the optimal static policy identifies the preferred intervention for each state. Finally, bootstrap policy stability analyses assess the consistency of these recommendations across repeated resampling, providing an indication of the robustness of the optimized policies.

Comparative Action Effects

Optimal policy selection

To address Research Question 2, the first step of the SEM-informed static policy optimization compared the relative advantage of alternative workplace-learning actions within each observed WBL–ACD state (Figure 4-18). Rather than evaluating actions using a single overall average, the figure presents each action's expected reward relative to the mean reward within the corresponding state. Positive values indicate that an action performed above the state-specific average, whereas negative values indicate below-average performance. Cells labeled Not observed represent WBL–ACD state-action combinations that were absent from the empirical data and therefore were not considered in the optimization.

Across the three cognitive domains, the comparative action profiles revealed that no single workplace-learning strategy consistently outperformed the others across all observed states. Instead, the relative advantage of each action varied according to the individual's WBL–ACD state. Among the observed states, digital learning most frequently demonstrated the largest

positive reward advantage, particularly within the High WBL–High ACD state, where it showed the greatest improvement across literacy, numeracy, and adaptive problem solving. Collaborative learning and training also produced positive advantages in several Mid WBL states, although these gains were generally smaller and more state-dependent. In contrast, the no-extra-support condition and blended high-WBL strategy were more often associated with neutral or slightly negative relative rewards.

Figure 4-18 Comparative advantage of workplace-learning actions relative to no extra support across observed WBL–ACD states.



Note.

The figure presents differences in SEM-informed estimated rewards for workplace-learning strategies relative to the observed no-extra-support baseline across selected Work-Based Learning (WBL) and Adult Cognitive Development (ACD) states for literacy, numeracy, and adaptive problem solving (APS). Positive values indicate higher estimated rewards than the baseline, whereas negative values indicate lower estimated rewards. Only states with an observed no-extra-support baseline are displayed. Reward differences represent cross-sectional, model-informed comparisons and should not be interpreted as causal intervention effects or predicted cognitive gains.

Although the numerical differences between actions were modest, the consistent variation across observed states indicates that workplace-learning strategies are not equally effective across all learner profiles. These findings provide the empirical justification for the subsequent static policy optimization, which identifies the workplace-learning action that maximizes the expected cognitive reward within each observed state. Consequently, the comparative action analysis demonstrates that optimizing workplace learning requires state-specific decision-making rather than the application of a single universal intervention.

Policy differentiation across WBL-ACD states

Figure 4.19 illustrates the extent to which the optimal workplace-learning action outperformed the second-best alternative across the observed WBL–ACD states for literacy, numeracy, and adaptive problem solving. The horizontal bars represent the difference in expected SEM-informed reward between the highest-ranked and second-highest-ranked workplace-learning action within each state. Larger gaps indicate clearer differentiation among competing actions and therefore greater confidence in the recommended policy, whereas smaller gaps indicate that multiple actions yield similar expected rewards.

Across all three cognitive domains, the High WBL–High ACD state exhibited the largest policy advantage. In this state, digital learning was consistently identified as the optimal workplace-learning strategy, producing the greatest separation from the second-best alternative. The largest advantage was observed for numeracy (approximately 0.02), followed by adaptive problem solving (approximately 0.02) and literacy (approximately 0.01). These findings suggest that the preferred intervention for individuals with high workplace-learning engagement and high cognitive proficiency is relatively robust because alternative actions provide noticeably lower expected reward.

Figure 4-19 Difference between the optimal and second-best workplace-learning actions across observed WBL–ACD states.



Note.

The figure presents the difference in SEM-informed static rewards between the highest-ranked and second-highest-ranked workplace-learning actions within selected Work-Based Learning–Adult Cognitive Development (WBL–ACD) states across literacy, numeracy, and adaptive problem solving (APS). Larger gaps indicate clearer differentiation between the two highest-ranked actions, whereas smaller gaps indicate that the rankings may be sensitive to modest reward variations. Values are rounded to two decimal places; displayed values of 0.00 may represent small positive differences. The results reflect cross-sectional, model-informed comparisons and should not be interpreted as causal intervention effects or predicted cognitive gains.

In contrast, the remaining observed states demonstrated substantially smaller policy gaps. Within the Mid WBL–High ACD state, training emerged as the preferred strategy for literacy

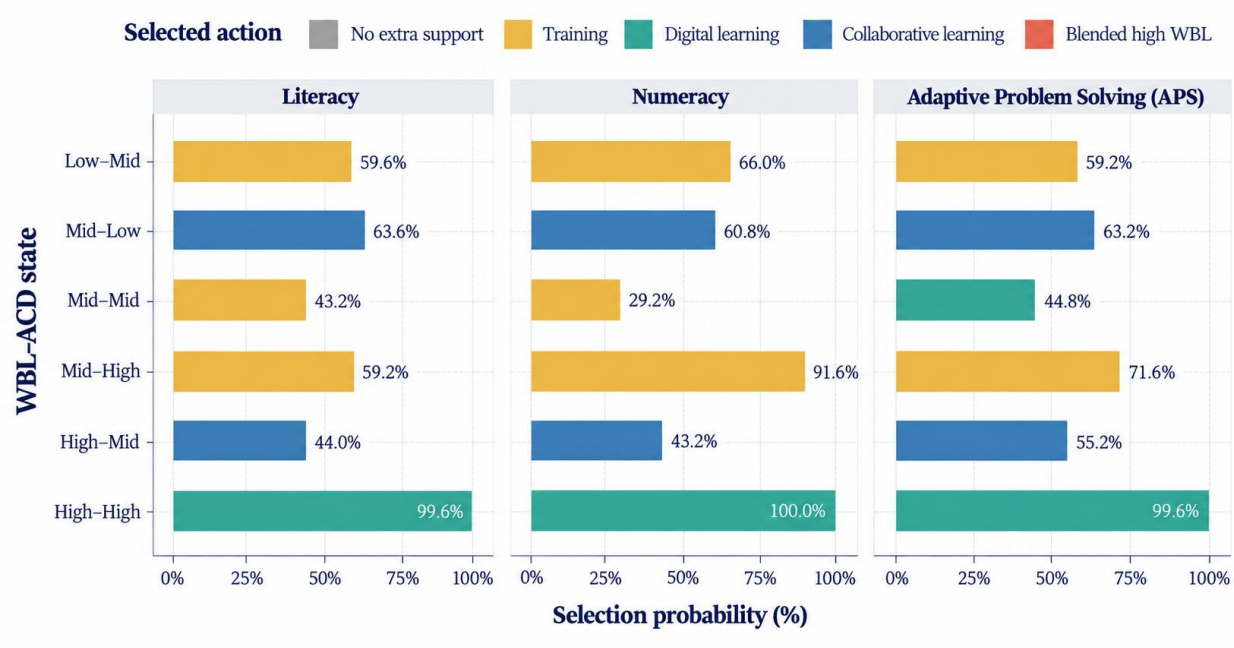
and numeracy, whereas collaborative learning was selected for adaptive problem solving; however, the differences between the best and second-best actions were minimal. Similarly, the Mid WBL–Mid ACD state produced only marginal differences among candidate actions, with training recommended for literacy and digital learning recommended for adaptive problem solving. The small reward gaps indicate that several workplace-learning strategies produced comparable expected outcomes within these states.

Overall, Figure 4.19 demonstrates that the certainty of the recommended workplace-learning strategy varies across WBL–ACD states. Strong policy differentiation was evident primarily within the High WBL–High ACD state, whereas the remaining observed states showed relatively small differences between competing actions. Consequently, the optimization results suggest that although state-specific workplace-learning recommendations can be identified, some recommendations are substantially more robust than others. This observation complements the subsequent bootstrap policy stability analysis by indicating where the optimized policies are most and least distinct.

Bootstrap policy stability

To evaluate the robustness of the SEM-informed static policy optimization, the optimal workplace-learning policy was re-estimated across 250 bootstrap samples for each cognitive domain (Figure 4-20). The stacked bars show the proportion of bootstrap samples in which each workplace-learning action was selected as the optimal policy within each observed WBL–ACD state. Higher selection probabilities indicate greater confidence that a particular action consistently maximizes the expected cognitive reward, whereas more evenly distributed probabilities indicate that multiple actions yield similar expected rewards.

Figure 4-20 Bootstrap stability of optimal workplace-learning policy selection across observed WBL–ACD state.



Note.

The figure presents the percentage of 250 bootstrap replications in which each displayed workplace-learning action was selected as the optimal strategy within a given Work-Based Learning–Adult Cognitive Development (WBL–ACD) state. Higher percentages indicate greater stability of the selected action across bootstrap samples, whereas lower percentages suggest greater uncertainty in the optimal action ranking. Digital learning demonstrated particularly high selection stability in the High–High state across literacy (99.6%), numeracy (100.0%), and APS (99.6%). These results reflect the reproducibility of model-informed static action rankings and do not establish causal effectiveness or predicted improvements in cognitive proficiency.

Across all three cognitive domains, the High WBL–High ACD state exhibited the greatest policy stability. Digital learning was selected as the optimal action in 99.6% of bootstrap samples for literacy, 100.0% for numeracy, and 99.6% for adaptive problem solving, indicating an exceptionally robust recommendation. In contrast, several intermediate states demonstrated greater variability in policy selection. For example, within the High WBL–Mid ACD state, collaborative learning was selected in 44.0% of literacy samples, 43.2% of numeracy samples, and 55.2% of APS samples, while training and blended workplace learning were also selected

with substantial frequency, indicating that these competing strategies produced comparable expected rewards.

Training exhibited consistently high selection probabilities in the Mid WBL–High ACD state, accounting for 59.2% of literacy bootstrap samples, 91.6% of numeracy samples, and 71.6% of APS samples. Similarly, training was the predominant recommendation within the Low WBL–Mid ACD state, with selection probabilities of 59.6% for literacy, 66.0% for numeracy, and 59.2% for APS. In contrast, the Mid WBL–Low ACD state consistently favored collaborative learning, which was selected in 63.6%, 60.8%, and 63.2% of bootstrap samples for literacy, numeracy, and APS, respectively.

The Mid WBL–Mid ACD state displayed the greatest uncertainty across domains. For literacy, training (43.2%), blended workplace learning (31.2%), and digital learning (23.2%) were all selected with appreciable frequency. A similar pattern emerged for numeracy, where training (29.2%), blended workplace learning (28.4%), and digital learning (25.6%) produced comparable selection probabilities. For APS, digital learning (44.8%) and training (44.0%) were selected at nearly identical rates, indicating that these actions generated very similar expected rewards.

Overall, the bootstrap analyses indicate that the stability of the optimized workplace-learning recommendations varies across WBL–ACD states. Recommendations were highly stable for the High WBL–High ACD state and generally moderately stable for the Low WBL–Mid ACD, Mid WBL–Low ACD, and Mid WBL–High ACD states. In contrast, the Mid WBL–Mid ACD state exhibited substantial policy uncertainty because several workplace-learning strategies yielded comparable expected rewards. These findings suggest that the SEM-informed static policy optimization provides robust recommendations in well-defined cognitive states

while identifying intermediate states in which multiple workplace-learning strategies may be similarly effective.

Integrated answer to the research questions

This study examined the relationship between work-based learning (WBL) and adult cognitive development (ACD) through two complementary research questions. Together, the findings demonstrate not only that WBL and ACD are closely interconnected, but also that this relationship can be translated into evidence-informed workplace-learning recommendations through SEM-informed static policy optimization.

Research Question 1 examined the nature of the reciprocal association between WBL and ACD. Across literacy, numeracy, and adaptive problem solving, the comparative SEM analyses consistently demonstrated that WBL and ACD are statistically interconnected. The Forward Recursive Mediation SEM identified significant positive associations from WBL to ACD, whereas the Reverse SEM supported positive associations from ACD to WBL. Reciprocal SEM specifications produced consistent directional patterns across cognitive domains, although these models also exhibited estimation instability and identification challenges. Consequently, the findings are interpreted as evidence of a robust reciprocal association and statistical interdependence between WBL and ACD rather than definitive evidence of stable simultaneous reciprocal effects. Mediation analyses further indicated that involvement in improving work organization or work processes partially explained this relationship, while robustness analyses using two-stage least squares demonstrated that the principal conclusions remained consistent across alternative estimation approaches.

Building upon these structural findings, Research Question 2 examined how different workplace-learning strategies influence adult cognitive development using a SEM-informed

static policy optimization framework. Rather than identifying a single universally optimal intervention, the optimization demonstrated that the effectiveness of workplace-learning strategies depends on the learner's existing WBL–ACD state. Comparative action analyses showed that the relative advantage of candidate workplace-learning strategies varied across cognitive states, supporting the need for individualized rather than uniform interventions. The optimized policies indicated that digital learning was consistently preferred for individuals with high workplace-learning engagement and high cognitive proficiency, whereas training-oriented and collaborative workplace-learning strategies were more frequently recommended for intermediate cognitive states. Bootstrap analyses further demonstrated that recommendations for high-performing states were highly stable across repeated resampling, while intermediate states exhibited greater uncertainty because several workplace-learning strategies produced comparable expected rewards.

Taken together, the findings from both research questions suggest that workplace learning can be conceptualized as a dynamic component of adult cognitive development rather than as a one-directional educational input. The structural equation models establish that WBL and ACD are closely interconnected across multiple dimensions of cognitive functioning, while the SEM-informed static policy optimization translates these empirical relationships into practical, state-specific workplace-learning recommendations. Collectively, the results demonstrate that tailoring workplace-learning opportunities to individuals' existing cognitive profiles has the potential to improve expected cognitive outcomes more effectively than adopting a single standardized workplace-learning strategy across the workforce.

Chapter 5 - Discussion

Introduction

This chapter interprets the results in relation to the study's research questions, the broader WBL-ACD framework, and the practical problem of designing adult learning systems that are actually responsive to workers' needs. The findings do not support a simplistic story in which workplace learning automatically and uniformly upgrades adult cognition. Instead, they support a more conditional account where cognitive resources and workplace learning opportunities appear to be connected, but that connection is shaped by model specification, sector context, and the worker's starting position in the joint WBL-ACD state space.

Generalizability of the Findings and Implications for Static Policy Optimization

The comparison between the analytic and full samples is important for interpreting the SEM-Informed Static Policy Optimization findings. Although the analytic sample remains broadly comparable by gender, it is more selective by education, occupation, and sector. Adults with higher education and clearly classified occupational or sectoral positions are more represented in the analytic sample, while respondents with lower education or missing occupational information are less represented. This matters because education, occupation, and sector are directly related to both workplace-based learning opportunities and adult cognitive development outcomes.

For the SEM-informed static policy optimization component, the optimal policy recommendations should be interpreted within the context of the employed adult population represented in the analytical sample rather than as universal recommendations for all adults. Because optimization is informed by cross-sectional associations estimated through SEM, the recommended workplace-learning actions reflect the observed characteristics and learning

conditions of the study population. Consequently, the findings provide evidence-based guidance for optimizing workplace-learning strategies among employed adults but should be interpreted with appropriate caution when generalized to populations or contexts beyond those represented in the PIAAC 2023 analytical sample.

Discussion of Data Characteristics and Quality

The data quality assessments demonstrated that the analytical sample was suitable for estimating the proposed SEM and SEM-informed static policy optimization models. Restricting the analysis to employed adults and applying multiple imputation preserved the final analytical sample while maintaining demographic and workforce characteristics comparable to those of the eligible U.S. PIAAC population. This suggests that the inclusion criteria and missing-data procedures did not materially affect the representativeness of the study sample, thereby supporting the external validity of the findings (Little & Rubin, 2019).

Multiple imputation successfully preserved the distributional characteristics of the study variables and generated plausible values for missing observations. The close agreement between observed and imputed distributions, together with the preservation of the correlation structure, indicates that the imputation procedure maintained both the univariate and multivariate properties of the dataset. These findings are consistent with recommendations that properly specified multiple imputation reduces bias while preserving statistical relationships necessary for multivariate analyses such as structural equation modeling (Rubin, 1987; Enders, 2022).

The psychometric evaluation further supported the adequacy of the workplace learning construct. Both the full and refined WBL measures demonstrated acceptable internal consistency, and the confirmatory factor analyses indicated that the retained indicators adequately represented the underlying construct. Although the refined measure exhibited slightly

lower reliability than the full measure, it provided a more parsimonious specification while maintaining acceptable construct validity. This finding aligns with recommendations that theoretically meaningful and parsimonious measurement models often improve model interpretability without substantially compromising reliability (Hair et al., 2022; Kline, 2023).

Overall, the data quality diagnostics provide confidence that the observed structural relationships are unlikely to be artifacts of poor measurement quality or inappropriate handling of missing data. Consequently, the subsequent findings regarding the nature of reciprocal association between workplace learning and adult cognitive development, and the identification of optimal workplace-learning actions through SEM-informed static policy optimization, can be interpreted with greater confidence.

Discussion of Research Question 1

The reciprocal association between WBL and ACD

WBL and ACD are statistically interconnected

A central finding of this study is that work-based learning (WBL) and adult cognitive development (ACD) are closely interconnected across literacy, numeracy, and adaptive problem solving. Across the competing simultaneous equation model (SEM) specifications, evidence consistently supported significant associations between workplace learning and cognitive performance, although the magnitude and direction of these associations varied across model specifications. The Forward Recursive Mediation SEM identified positive associations from WBL to ACD, whereas the Reverse SEM supported positive associations from ACD to WBL. Although the reciprocal SEMs produced larger standardized coefficients, these models also exhibited estimation instability, indicating that the relationship is more appropriately interpreted as one of statistical interdependence rather than definitive evidence of stable simultaneous

reciprocal effects. Collectively, the convergence of findings across multiple SEM specifications suggests that workplace learning and adult cognitive development should be viewed as closely related components of lifelong learning and workforce development.

These findings are consistent with theories of adult learning that emphasize the continuous development of knowledge and skills through experience and workplace participation. Knowles (1984) argued that adults learn most effectively when learning is relevant to their professional responsibilities and immediately applicable to authentic problems. Similarly, Kolb (1984) proposed that learning occurs through cycles of concrete experience, reflection, conceptualization, and experimentation, while Billett (2001, 2011) emphasized that workplaces function as important learning environments in which everyday work activities contribute to ongoing cognitive development. Collectively, these theoretical perspectives suggest that learning is embedded within workplace practice rather than being confined to formal educational settings, supporting the present finding that workplace learning is associated with broader measures of adult cognitive proficiency.

The findings also align with evidence from the Programme for the International Assessment of Adult Competencies (PIAAC), which has consistently demonstrated positive associations between workplace learning opportunities, skill use, and adult proficiency in literacy, numeracy, and problem solving (OECD, 2013, 2019, 2024). However, much of the existing literature has examined this relationship from a single directional perspective, typically investigating either how workplace learning contributes to skill development (e.g., Billett, 2001; Eraut, 2004) or how individuals with higher cognitive skills are more likely to participate in learning-intensive work environments (OECD, 2019; Desjardins, 2017). Consequently, the reciprocal nature of the relationship has received comparatively little empirical attention.

The present study extends this literature by evaluating multiple competing SEM specifications rather than relying on a single structural model. Instead of assuming one causal direction, the analyses compared forward recursive, reverse recursive, reciprocal, correlated-disturbance, refined latent, and instrumental-variable specifications to examine the consistency of the observed relationships. This comparative modeling strategy demonstrated that the association between WBL and ACD remained evident across alternative theoretical and statistical assumptions, thereby providing stronger evidence for their interconnectedness than would have been obtained from a single-model analysis. At the same time, the estimation instability observed in several reciprocal SEMs underscores the importance of interpreting the relationship as one of robust statistical interdependence rather than definitive reciprocal causation.

Taking together, these findings suggest that workplace learning should be conceptualized as an integral component of adult cognitive development rather than merely an outcome of prior education or occupational experience. Adults continuously acquire, apply, and refine cognitive skills through workplace participation, while existing cognitive capabilities simultaneously shape individuals' ability to engage in and benefit from workplace-learning opportunities. This dynamic relationship provides the empirical foundation for the SEM-informed static policy optimization developed in this dissertation, which translates these structural associations into evidence-informed workplace-learning recommendations tailored to different learner profiles.

Interpreting the Reciprocal Association: Evidence of Statistical Interdependence Rather Than Definitive Reciprocal Association

One of the most important findings of this study is that the relationship between work-based learning (WBL) and adult cognitive development (ACD) is best understood as one of

statistical interdependence rather than definitive reciprocal causality. Although the reciprocal SEM specifications consistently estimated positive ACD → WBL pathways and negative WBL → ACD pathways across literacy, numeracy, and adaptive problem solving, these models also produced estimation warnings, including non-positive definite parameter covariance matrices and standardized coefficients approaching or exceeding an absolute value of one. Such diagnostic patterns indicate that the reciprocal models experienced identification strain and numerical instability, suggesting that the resulting coefficients should be interpreted cautiously.

This interpretation is consistent with established SEM methodology. Kline (2023) notes that nonrecursive structural equation models require strong identification conditions and theoretically defensible instrumental variables to produce stable and interpretable reciprocal estimates. Similarly, Bollen (1989) emphasized that reciprocal models are substantially more demanding than recursive models because simultaneous feedback structures increase the complexity of model identification and estimation. Hayduk (1987) further argued that reciprocal relationships should be interpreted within the broader context of theoretical plausibility and model identification rather than solely based on statistical significance. Collectively, these methodological perspectives suggest that reciprocal SEMs can provide valuable evidence regarding the potential interdependence of constructs but should not be interpreted as conclusive evidence of simultaneous causal feedback without strong identification and supporting longitudinal or experimental data.

An additional methodological consideration concerns the numerical identification and estimation stability of the reciprocal SEM specifications. Although all 21 SEM specifications converged across the three cognitive domains, each generated a warning indicating that the estimated parameter variance-covariance matrix was not positive definite. Furthermore, several

standardized reciprocal path coefficients approached or exceeded an absolute value of 1.00, particularly for literacy and adaptive problem solving. These findings raise concerns about parameter identification and the reliability of model-based inference. Accordingly, the consistently opposing directional coefficients should be interpreted as model-specific statistical associations rather than definitive evidence of reciprocal causality or a stable mutually reinforcing relationship (Bollen, 1989; Nagase & Kano, 2017).

The findings of the present study closely reflect these methodological considerations. Although the reciprocal SEMs demonstrated remarkably consistent directional patterns across literacy, numeracy, and adaptive problem solving, the accompanying estimation diagnostics indicated that the largest reciprocal coefficients were also the least numerically stable. In contrast, the Forward Recursive SEM, Reverse SEM, Correlated Disturbance SEM, and instrumental-variable robustness analyses all consistently supported the existence of a close association between WBL and ACD under alternative modeling assumptions. The convergence of these complementary models therefore provides stronger evidence than any single reciprocal specification alone.

An important contribution to this dissertation is that it does not rely on a single reciprocal SEM to support its conclusions. Previous studies examining workplace learning and adult skills have typically estimated one-directional pathways, assuming either that workplace learning enhances cognitive skills (Billett, 2001; Eraut, 2004) or that individuals with stronger cognitive skills are more likely to participate in workplace learning (OECD, 2019; Desjardins, 2017). In contrast, the present study systematically compared forward recursive, reverse recursive, correlated-disturbance, reciprocal, refined latent, and instrumental-variable SEM specifications. This comparative modeling strategy demonstrated that the association between WBL and ACD

remained evident across multiple theoretical and statistical assumptions, while also identifying the limitations of relying exclusively on reciprocal models. Consequently, the principal conclusion of this study is based on the convergence of evidence across competing SEM specifications rather than on any single model.

Taken together, these findings suggest that workplace learning and adult cognitive development operate as mutually interconnected components of adult learning, while acknowledging that the precise magnitude of simultaneous reciprocal effects cannot be established using cross-sectional data alone. By distinguishing statistical interdependence from reciprocal causality, this study provides a more cautious and methodologically defensible interpretation of the WBL–ACD relationship. This distinction not only strengthens the credibility of the findings but also establishes a rigorous empirical foundation for the SEM-informed static policy optimization developed in Research Question 2.

Role of workplace participation

The mediation analyses suggest that participation in improving work organization or work processes represents an important mechanism linking work-based learning (WBL) and adult cognitive development (ACD). Across the three cognitive domains, the Forward Recursive Mediation SEM indicated that workplace participation partially explained the association between WBL and cognitive outcomes, although the strength of this mechanism varied across literacy, numeracy, and adaptive problem solving. Significant indirect effects were observed for literacy and adaptive problem solving, whereas the indirect pathway for numeracy was comparatively weaker. These findings suggest that workplace learning influences adult cognitive development not only through direct learning experiences but also through opportunities for employees to participate actively in organizational improvement processes.

This finding is consistent with experiential learning theory, which proposes that meaningful learning occurs when individuals engage in authentic work experiences, reflect on those experiences, and apply new knowledge to solve practical problems (Kolb, 1984). Improving work organization or work processes requires employees to evaluate existing practices, identify opportunities for improvement, and implement new solutions. These activities involve critical thinking, problem solving, communication, and reflection, all of which are fundamental components of adult cognitive development. Rather than functioning solely as recipients of workplace training, employees become active participants in organizational learning, thereby creating additional opportunities for cognitive growth.

The findings also align with situated learning theory, which argues that learning is embedded within the social and organizational context in which work occurs (Lave & Wenger, 1991). From this perspective, cognitive development is not acquired exclusively through formal instruction but emerges through participation in authentic workplace practices. Employees who contribute to improving work processes are engaged in legitimate workplace activities that require them to apply existing knowledge while simultaneously acquiring new competencies. Consequently, participation in organizational improvement may represent an important pathway through which workplace experiences contribute to adult learning beyond formal training programs.

Similarly, the results support the concept of communities of practice (Wenger, 1998), which emphasizes that learning occurs through collaboration, shared problem solving, and participation in collective workplace activities. Organizational improvement initiatives typically require employees to exchange ideas, coordinate with colleagues, and develop shared solutions to workplace challenges. These collaborative processes create opportunities for reflection,

knowledge sharing, and continuous learning, thereby reinforcing both individual cognitive development and organizational learning. The finding that workplace participation contributes to literacy and adaptive problem solving is therefore consistent with the view that learning is fundamentally a social and participatory process rather than an individual cognitive activity alone.

An important contribution of this study is that it extends previous workplace-learning research by examining how the relationship between WBL and ACD operates rather than simply demonstrating that an association exists. Previous studies have generally focused on direct relationships between workplace learning and adult skills (Billett, 2001; Eraut, 2004; OECD, 2019), with comparatively less attention devoted to the mechanisms through which workplace experiences support cognitive development. By incorporating organizational improvement as a mediator, this study demonstrates that workplace participation constitutes one pathway through which learning opportunities may be translated into broader cognitive outcomes. At the same time, the relatively modest indirect effects indicate that workplace participation explains only part of the overall relationship, suggesting that other organizational, motivational, and contextual factors also contribute to adult cognitive development.

Overall, these findings reinforce the view that workplace learning should be understood as a participatory process rather than simply the provision of training opportunities. Opportunities to contribute to improving work organization appear to create additional learning experiences that complement formal workplace learning and support the continued development of adult cognitive skills. Consequently, organizations seeking to strengthen workforce capability should consider not only expanding access to workplace-learning opportunities but also creating

environments in which employees can actively participate in improving work practices, solving organizational problems, and contributing to continuous workplace innovation.

Robustness of the WBL–ACD Relationship Across Alternative Model Specifications

A key strength of this study is that the principal findings were evaluated across multiple analytical approaches rather than relying on a single structural model. In addition to comparing alternative SEM specifications, the study assessed the robustness of the findings using an instrumental-variable approach (Model 8), multiple plausible values for cognitive proficiency, and survey-weighted estimation procedures. Collectively, these analyses demonstrated that the observed relationship between work-based learning (WBL) and adult cognitive development (ACD) was not dependent on a single modeling strategy, thereby increasing confidence in the substantive conclusions.

The instrumental-variable analysis provided an important robustness assessment because it evaluated the WBL–ACD relationship under a different set of statistical assumptions. Although the magnitude of the coefficients differed from those obtained using the SEMs, the overall pattern remained consistent. Across literacy, numeracy, and adaptive problem solving, the ACD → WBL pathway remained positive and statistically significant, whereas the WBL → ACD pathway was comparatively smaller and not statistically significant under the two-stage least squares specification. Rather than contradicting the SEM findings, these results suggest that the observed relationship between workplace learning and adult cognitive development is robust, while also indicating that the strength of the directional pathways depends on the underlying modeling assumptions.

The use of multiple plausible values further strengthens the credibility of the findings. PIAAC assesses literacy, numeracy, and adaptive problem solving using plausible values to

account for measurement uncertainty in proficiency estimation (OECD, 2024). Rather than relying on a single proficiency estimate, this study pooled results across all plausible values using Rubin's rules, thereby incorporating measurement uncertainty directly into the parameter estimates. The consistency of the findings across plausible values indicates that the substantive conclusions were not influenced by any single imputed proficiency score.

Similarly, the analyses incorporated Fay's balanced repeated replication (BRR) weights to account for the complex sampling design of PIAAC. Survey-weighted estimation produced standard errors that appropriately reflected sampling variability while preserving the overall pattern of relationships observed across the competing SEM specifications. Consequently, the findings are representative of the target adult population rather than being limited to the observed sample.

An important methodological contribution of this dissertation is therefore its emphasis on triangulation across analytical approaches. Previous studies examining workplace learning and adult skills have typically relied on a single statistical framework to evaluate the relationship between workplace learning and cognitive outcomes (e.g., Billett, 2001; Desjardins, 2017; OECD, 2019). In contrast, the present study systematically compared multiple SEM specifications, incorporated mediation analyses, evaluated instrumental-variable robustness, and accounted for measurement and sampling uncertainty through plausible values and survey weights. The consistency of the principal findings across these complementary analytical approaches provides stronger evidence for the interconnected relationship between WBL and ACD than would have been obtained from any single method alone.

However, the robustness analyses provide additional qualifications regarding the directionality of the WBL–ACD relationship. Although the reciprocal path estimates retained

consistent directional signs across the examined plausible values and imputed datasets, this consistency does not independently establish model identification or causal direction. Furthermore, the two-stage least-squares estimates depend on the relevance and validity of the specified instrumental variables, including the assumption that excluded instruments affect the outcome only through the modeled endogenous predictor. Consequently, the positive ACD → WBL estimates observed in the 2SLS specification provide conditional support for directional asymmetry but are not interpreted as definitive causal effects. Taken together, the robustness analyses strengthen confidence in the descriptive consistency of certain association patterns while leaving the causal interpretation unresolved.

Overall, the robustness analyses demonstrate that the principal conclusions of this study are not model-dependent. Although individual coefficients varied across estimation methods, the overarching conclusion that workplace learning and adult cognitive development are closely interconnected remained consistent. This convergence across multiple analytical approaches increases confidence in the validity of the findings and provides a strong empirical foundation for the SEM-informed static policy optimization developed in Research Question 2.

Summary RQ 1

Research Question 1 examined the nature of the reciprocal association between work-based learning (WBL) and adult cognitive development (ACD). Across literacy, numeracy, and adaptive problem solving, the findings consistently demonstrated that WBL and ACD are closely interconnected, although the strength and direction of the associations varied across alternative structural equation model specifications. Comparative model evaluation showed that no single SEM provided a universally superior representation of the data. Instead, the convergence of evidence across forward recursive, reverse recursive, correlated-disturbance, reciprocal, and

instrumental-variable models supports the conclusion that WBL and ACD are characterized by robust statistical interdependence rather than definitive simultaneous reciprocal causality.

The mediation analyses further indicated that participation in improving work organization or work processes partially explained the relationship between WBL and ACD, suggesting that workplace participation represents one mechanism through which workplace learning is associated with adult cognitive development. Robustness analyses using instrumental-variable estimation, plausible values, and survey-weighted procedures demonstrated that the principal findings remained consistent across alternative analytical approaches, increasing confidence in the stability of the observed relationships.

Collectively, these findings extend the workplace-learning literature by moving beyond the traditional examination of a single directional relationship. Rather than assuming that workplace learning influences cognitive development or vice versa, this study systematically evaluated multiple competing SEM specifications to demonstrate that WBL and ACD are empirically interconnected across multiple cognitive domains. This comprehensive evaluation provides the theoretical and empirical foundation for Research Question 2, which translates these structural relationships into evidence-informed workplace-learning recommendations through SEM-informed static policy optimization.

Discussion of Research Question 2

Implications of SEM-informed static policy optimization

No universal learning strategy

The SEM-informed static policy optimization demonstrated that no single workplace-learning strategy consistently maximized expected cognitive outcomes across all observed WBL–ACD states. Instead, the optimal intervention depended on an individual's existing

combination of workplace-learning engagement and cognitive proficiency. Comparative action analyses showed that the relative advantage of training, digital learning, collaborative learning, and blended workplace-learning strategies varied across observed states, while bootstrap analyses further confirmed that several intermediate states exhibited comparable probabilities across competing interventions. These findings indicate that workplace learning is context-dependent, suggesting that a uniform workplace-learning strategy is unlikely to be equally effective for all employees.

This finding is consistent with contemporary theories of adult learning, which argue that learning effectiveness depends on learners' existing knowledge, experiences, and learning contexts rather than on standardized instructional approaches (Knowles, 1984; Merriam & Bierema, 2014). Similarly, adaptive learning frameworks emphasize that instructional decisions should respond to learners' individual characteristics rather than assuming that identical interventions will produce equivalent outcomes (UNESCO, 2021). The present findings extend these perspectives by demonstrating that state-specific workplace-learning recommendations can be generated empirically using observed workforce data rather than relying solely on theoretical assumptions.

Previous workplace-learning studies have generally examined whether workplace learning contributes to skill development (Billett, 2001; Eraut, 2004; OECD, 2019), but comparatively few have investigated which workplace-learning strategy is most appropriate for different learner profiles. The present study therefore contributes to the literature by moving beyond explanation toward evidence-informed decision support, demonstrating that workplace-learning interventions should be aligned with employees' existing WBL–ACD states rather than implemented uniformly across the workforce.

Digital Learning Emerges as the Preferred Strategy for High WBL–High ACD States

One of the most consistent findings of the optimization was the recommendation of digital learning for individuals classified within the High WBL–High ACD state. Across literacy, numeracy, and adaptive problem solving, digital learning generated the highest expected cognitive rewards and exhibited exceptionally high bootstrap selection probabilities, indicating that this recommendation was highly robust. The clear separation between the optimal and second-best actions further suggests that digital learning provides distinct advantages for individuals who already demonstrate strong workplace-learning engagement and cognitive proficiency.

This finding aligns with research indicating that digitally enriched learning environments are most effective when learners possess sufficient cognitive resources and self-directed learning capabilities (OECD, 2021; van Laar et al., 2020). Adults with stronger cognitive skills are generally better equipped to navigate technology-rich environments, evaluate complex information, and regulate their own learning processes. Consequently, digital workplace-learning opportunities may enable these individuals to extend existing competencies through greater flexibility, access to information, and continuous learning opportunities.

The findings also support theories of self-directed learning (Knowles, 1984), which suggest that experienced learners benefit from greater autonomy in selecting learning resources and managing their own professional development. Rather than replacing traditional workplace learning, digital learning appears to complement existing cognitive strengths by providing opportunities for continuous knowledge acquisition and problem solving within authentic workplace contexts.

Training and Collaborative Learning Remain Important for Intermediate WBL–ACD States

In contrast to the high-performing states, individuals classified within intermediate WBL–ACD states were more frequently assigned training-oriented or collaborative workplace-learning strategies. Training predominated in several Mid WBL–High ACD and Low WBL–Mid ACD states, whereas collaborative learning was more frequently recommended within Mid WBL–Low ACD states. These recommendations suggest that employees with developing workplace-learning engagement or cognitive proficiency may benefit from greater instructional structure and social interaction before transitioning toward more autonomous learning approaches.

These findings are consistent with experiential and social theories of workplace learning. Billett (2001) argued that structured workplace experiences provide important opportunities for developing occupational competence, particularly for learners who are still building professional expertise. Similarly, Wenger (1998) emphasized that learning occurs through participation in communities of practice, where collaboration and shared problem solving facilitate the development of knowledge and professional identity. Collaborative workplace learning therefore provides opportunities for employees to observe, discuss, and apply knowledge within authentic organizational settings, supporting the gradual development of higher-order cognitive skills.

An important implication of these findings is that workplace-learning strategies should evolve alongside employees' learning trajectories. Rather than assuming that advanced digital learning environments are equally appropriate for all employees, organizations should consider sequencing workplace-learning opportunities according to individuals' existing cognitive capabilities and workplace-learning experiences.

Policy Stability of Optimized Workplace-Learning Recommendations

An important contribution of this study is that the optimized workplace-learning recommendations were evaluated using bootstrap resampling rather than relying solely on a single optimization solution. Across the observed WBL–ACD states, policy stability varied considerably. Recommendations for the High WBL–High ACD state demonstrated exceptionally high stability across all three cognitive domains, whereas several intermediate states exhibited greater uncertainty because multiple workplace-learning strategies produced comparable expected rewards.

These findings have important practical implications. High policy stability indicates that the recommended intervention consistently maximizes expected cognitive outcomes despite sampling variation, thereby increasing confidence in its implementation. Conversely, lower stability should not be interpreted as evidence of poor model performance. Instead, it suggests that several workplace-learning strategies may be similarly effective within those cognitive states, providing organizations with greater flexibility when selecting interventions. Such flexibility may be advantageous because workplace-learning decisions are often influenced by organizational resources, technological infrastructure, and workforce characteristics that extend beyond statistical optimization alone.

From a methodological perspective, incorporating bootstrap stability analyses extends previous workplace-learning research by explicitly evaluating the reliability of optimized policy recommendations. Many optimization studies report only the single best intervention without assessing how consistently that intervention would be selected under repeated sampling. By quantifying policy stability, the present study provides decision makers with information regarding both which intervention is preferred and how confident they should be in that

recommendation. This additional layer of evidence strengthens the practical value of the SEM-informed static policy optimization framework.

Summary RQ 2

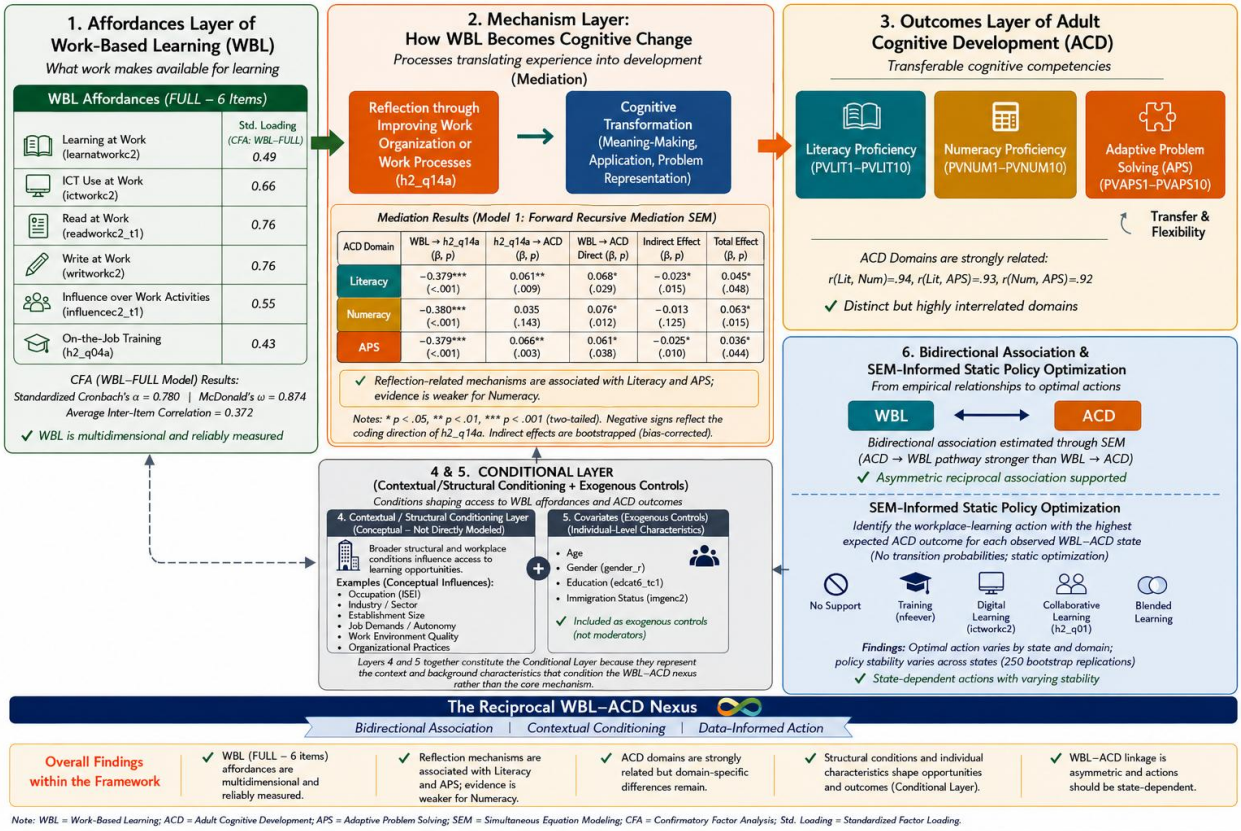
Research Question 2 examined how different workplace-learning strategies influence adult cognitive development using a SEM-informed static policy optimization framework. The findings demonstrated that the effectiveness of workplace-learning interventions depends on individuals' existing WBL–ACD states rather than on a universally optimal learning strategy. Digital learning consistently emerged as the preferred intervention for individuals with high workplace-learning engagement and cognitive proficiency, whereas training-oriented and collaborative workplace-learning strategies were more frequently recommended for intermediate states. Bootstrap analyses further showed that recommendations for high-performing states were highly stable, while intermediate states exhibited greater uncertainty because several interventions produced comparable expected rewards. Collectively, these findings demonstrate that tailoring workplace-learning opportunities to employees' cognitive profiles has the potential to improve expected cognitive outcomes more effectively than implementing a uniform workplace-learning strategy across the workforce.

Interpreting the Findings through the WBL-ACD Framework

The empirical findings can be interpreted through the six layers of the revised WBL-ACD Framework presented in Figure 5-1. Collectively, the findings provide evidence that workplace learning and adult cognitive development are interconnected, but they also refine the original expectation of a uniformly reinforcing relationship. The results indicate that the WBL-ACD nexus is better understood through three overarching principles: reciprocal association, conditional context, and state-dependent action. In particular, the competing SEM specifications

suggest an asymmetric reciprocal relationship, while the SEM-informed static policy optimization demonstrates that the workplace-learning action associated with the highest expected cognitive outcome depends on an adult's observed WBL-ACD state.

Figure 5-1 Revised WBL-ACD Framework with Findings



Affordances Layer of Work-Based Learning (WBL)

The Affordances Layer (Box numbered 1 in Figure 5-1) represents what the workplace makes available for learning and is operationalized in the full WBL construct through Learning at Work (learnatworkc2), ICT Use at Work (ictworkc2), Read at Work (readatworkc2_t1), Write at Work (writeatworkc2), On-the-Job-Training (h2_q04a), and Influence over Work Activities (influencec2_t1). These indicators capture complementary dimensions of workplace learning, including engagement in learning activities, interaction with digital resources, and opportunities to exercise influence and agency in work tasks.

The measurement results provide empirical support for conceptualizing WBL as a multidimensional construct comprising related workplace-learning affordances. In the six-item WBL Full CFA model, standardized factor loadings were 0.76 for Reading at Work, 0.76 for Writing at Work, 0.66 for ICT Use at Work, 0.55 for Influence over Work Activities, 0.49 for Learning at Work, and 0.43 for the sixth workplace-learning indicator. Reading and writing at work therefore exhibited the strongest relationships with the underlying WBL construct, followed by ICT use and influence over work activities, while learning at work and the sixth indicator contributed more moderately. The six-item measure also demonstrated acceptable internal consistency (standardized Cronbach's $\alpha = .780$; average inter-item correlation = .372). Collectively, these findings support the use of the full WBL measure and reinforce the framework's conceptualization of workplace learning as a set of complementary learning affordances rather than a single workplace activity.

Mechanism Layer: How WBL Becomes Cognitive Change

The Mechanism Layer (Box numbered 2 in Figure 5-1) represents the processes through which workplace-learning experiences may be translated into cognitive development. In the empirical model, this mechanism is represented by Reflection through Improving Work Organization or Work Processes (h2_q14a). Conceptually, involvement in improving work processes requires workers to examine existing practices, identify problems, consider alternatives, and apply knowledge to workplace situations.

The mediation results provided domain-specific rather than uniform support for this mechanism. WBL was significantly associated with the reflection-related measure across all three domain models (standardized $\beta \approx -0.379$, $p < .001$). The negative coefficient reflects the coding direction of h2_q14a and should therefore be interpreted according to the response coding

rather than as evidence that WBL reduces reflection. Reflection, in turn, was significantly associated with literacy (β = .061, p = .009) and adaptive problem solving (β = .066, p = .003), but its association with numeracy was not statistically significant (β = .035, p = .143). At the same time, WBL retained small but statistically significant direct associations with literacy (β = .068, p = .029), numeracy (β = .076, p = .012), and APS (β = .061, p = .038).

These findings therefore suggest that the proposed reflection mechanism is more evident for literacy and adaptive problem solving than for numeracy. This distinction is theoretically meaningful: participation in improving work organization or work processes may particularly engage interpretive, reflective, and adaptive forms of cognition, whereas numeracy may depend more strongly on other forms of workplace skill use or learning experience. The results consequently support the Mechanism Layer as a domain-sensitive pathway rather than a universal mechanism operating equally across all dimensions of ACD. Because the PIAAC data are cross-sectional, however, these pathways represent statistical associations consistent with mediation and should not be interpreted as evidence that WBL temporally produces reflection, which subsequently causes cognitive development.

Outcomes Layer of Adult Cognitive Development (ACD)

The Outcomes Layer (Box numbered 3 in Figure 5-1) represents the transferable cognitive competencies examined in the study: Literacy (PVLIT1-PVLIT10), Numeracy (PVNUM1-PVNUM10), and Adaptive Problem Solving (PVAPS1-PVAPS10). These domains capture different but closely related dimensions of adults' capacity to understand information, use quantitative reasoning, and adaptively address complex problems.

The descriptive results strongly demonstrated this interrelationship. Literacy and numeracy were correlated at approximately r = .94, literacy and APS at r = .93, and numeracy

and APS at r = .92. These strong correlations indicate substantial commonality across adult cognitive competencies while supporting their treatment as separate domain-specific outcomes. Analyzing the three domains separately also allowed the study to determine whether the WBL-ACD relationship and subsequent optimization recommendations were consistent across different forms of cognitive competence rather than assuming that all cognitive outcomes operate identically.

The Conditional Layer

Layers 4 and 5 (Box numbered 4 & 5 in Figure 5-1) are displayed separately in Figure 5-1 for analytical clarity but are interpreted collectively as the broader Conditional Layer of the WBL-ACD Framework. Their shared purpose is to recognize that workplace learning and adult cognitive development occur within social, educational, demographic, and workplace contexts rather than in isolation.

Structural Conditioning of WBL Affordances (Control)

The structural conditioning (Box numbered 4 in Figure 5-1) represents broader structural and contextual conditions that can shape adults' access to and quality of workplace-learning opportunities. Its theoretical purpose is to recognize that learning affordances are partly produced by the organization and structure of work. Workers may therefore encounter different opportunities for complex tasks, autonomy, technology use, collaboration, or workplace learning because of the environment in which they work.

This layer is important because the WBL-ACD framework does not conceptualize workplace learning exclusively as an individual choice. Opportunities to learn are also conditioned by the work environment. Consequently, observed differences in WBL should be

interpreted partly in relation to the structural availability of learning-rich work rather than solely as differences in workers' motivation or willingness to learn.

Covariates (Exogenous Controls)

The Covariates Layer (Box numbered 5 in Figure 5-1) represents the measured individual-level characteristics included in the statistical models: Age, Gender (gender_r), Educational Attainment (edcat6_tc1), self-reported health (i2_q03), and Immigration Status (imgenc2). These variables were included as exogenous controls to account for systematic differences that may be associated with both workplace-learning opportunities and adult cognitive outcomes.

Importantly, these characteristics are not modeled as moderators. The analysis therefore does not assume that, for example, gender or education changes the strength of the WBL → ACD relationship. Instead, these variables account for background differences so that the primary WBL-ACD structural associations can be interpreted conditionally on relevant observed characteristics.

Conceptually, merging structural conditioning factors and covariates as controls is useful because both address the conditions surrounding the WBL-ACD nexus rather than the mechanism through which WBL becomes ACD. Structural and contextual conditioning factors (Box 4 in Figure 5-1) represent structural and contextual conditions that can shape adults' access to and quality of workplace-learning opportunities, whereas covariates (Box 5 in Figure 5-1) represent measured individual-level exogenous conditioning. Together, they acknowledge that adults enter workplace-learning environments with different characteristics and encounter different opportunities for learning. Their separate visual presentation should nevertheless be

retained because they are analytically different. Thus, the framework recognizes conditional context without claiming moderation effects that were not empirically tested.

Bidirectional Association and SEM-Informed Static Policy Optimization

This layer (Box 6 in Figure 5-1) provides the empirical integration of the framework and contains two related but analytically distinct components: the bidirectional WBL-ACD association and SEM-informed static policy optimization.

Bidirectional Association: WBL ↔ ACD

The first component evaluates the central theoretical proposition that WBL and ACD are interconnected in both directions. Rather than estimating only a conventional WBL → ACD model, the study compared multiple competing SEM specifications representing forward, reverse, reciprocal, correlated-disturbance, observed-WBL, refined latent-WBL, strongly identified reciprocal, and 2SLS robustness specifications.

The results provide partial rather than symmetrical support for the reciprocal WBL-ACD nexus. Across competing specifications, the ACD → WBL relationship was generally stronger and more stable, whereas the WBL → ACD relationship was more sensitive to measurement and model specification. In particular, when WBL was modeled as an observed construct within the reciprocal specification, the WBL → ACD pathway moved toward non-significance.

These findings refined the theoretical framework. They suggest that WBL and ACD should not be interpreted as an equally balanced feedback cycle in which each necessarily increases the other over time. Instead, the evidence supports an asymmetric reciprocal association. Existing cognitive capacity may be particularly important in enabling adults to access, engage with, and potentially benefit from learning-rich work. In contrast, the relationship

between workplace learning and cognitive outcomes appears more conditional on how WBL and the structural relationship are specified.

This finding is theoretically important because it raises the possibility of cumulative advantage. Workers entering the workplace with stronger cognitive resources may be better positioned to undertake complex tasks, engage with technology, exercise influence over work activities, and participate in additional learning opportunities. In turn, workers with fewer cognitive resources may encounter fewer opportunities to enter these learning-rich environments, potentially reinforcing existing differences in workplace learning.

SEM-Informed Static Policy Optimization

The second component of Layer 6 translates the structural evidence into data-informed action. The WBL-ACD states were not generated by the SEM. Instead, standardized WBL and domain-specific ACD scores were divided into low, medium, and high tertiles, producing nine observed WBL-ACD states for each cognitive domain. Across literacy, numeracy, and APS, this generated 27 domain-specific state conditions.

Within these states, alternative workplace-learning actions, including No Support, Training (nfeever), Digital Learning (ictworkc2), Collaborative Learning (h2_q01), and Blended Learning, were evaluated according to their expected cognitive rewards. The WBL → ACD coefficient obtained from Model 1, the Forward Recursive Mediation SEM, informed the reward function. Thus, the broader competing SEM analysis addressed the reciprocal relationship in RQ1, while Model 1 supplied the directional structural information used for the RQ2 reward specification.

The optimization results showed that a single workplace-learning strategy was not optimal across all WBL-ACD states. Instead, the action associated with the highest expected

cognitive outcome varied according to an adult's observed position within the joint WBL-ACD state space and across cognitive domains. This finding provides direct empirical support for the framework's state-dependent action proposition: workplace-learning strategies should not necessarily be treated as universally beneficial regardless of workers' existing learning and cognitive conditions.

The 250 bootstrap replications per domain further showed that the stability of these recommendations varied across states. Some states produced a strongly dominant action, whereas others showed greater competition among alternative workplace-learning strategies. For example, the High-WBL/High-ACD states showed particularly strong stability around digital learning, whereas several intermediate states exhibited greater uncertainty across available actions. Consequently, the framework distinguishes not only which action appears optimal, but also how confidently that action can be identified from the observed data.

Importantly, Layer 6 does not represent reinforcement learning or longitudinal policy adaptation. No transition from to is modeled, and the analysis does not claim that workers move sequentially through WBL-ACD states following an intervention. Instead, it asks a cross-sectional decision question: given an observed WBL-ACD state, which workplace-learning action is associated with the highest expected cognitive outcome?

Summary interpretation of the revised WBL-ACD Framework

Taken together, the findings refine rather than reject the proposed WBL-ACD Framework. Layer 1 (Affordances) identifies the workplace-learning opportunities available to adults; Layer 2 (Mechanism) represents reflection as a process through which those experiences may be cognitively meaningful; and Layer 3 (Outcomes) captures literacy, numeracy, and adaptive problem solving as transferable cognitive competencies. Layers 4 (Controls) and 5

(Covariates) collectively form the Conditional Layer, recognizing that the WBL-ACD relationship is embedded within structural, demographic, and educational circumstances. Finally, Layer 6 empirically evaluates the reciprocal WBL-ACD relationship and translates the resulting structural information into state-specific workplace-learning recommendations.

The results therefore suggest that the WBL-ACD nexus is not best characterized as a deterministic cycle in which workplace learning automatically produces cognitive growth and cognitive growth automatically produces further workplace learning. Instead, it is better understood as an asymmetric reciprocal system operating within conditional contexts. Existing cognitive capabilities appear particularly important for engagement with workplace learning, while the potential contribution of WBL to ACD depends on measurement, model specification, and workers' observed WBL-ACD conditions. The static optimization results extend this conclusion by demonstrating that different WBL-ACD starting positions are associated with different preferred learning actions and different levels of policy stability.

Accordingly, empirical findings support three central principles represented at the base of the revised framework: Bidirectional Association, Contextual Conditioning, and Data-Informed Action. These principles represent the central refinement of the WBL-ACD Nexus emerging from the study: WBL and ACD are interconnected but asymmetrical; their relationship occurs within conditional social and workplace contexts; and the practical learning strategy associated with the most favorable cognitive outcome is state-dependent rather than universal.

Implications

This study makes several contributions to the workplace learning and adult education literature. First, it advances the understanding of the relationship between work-based learning (WBL) and adult cognitive development (ACD) by demonstrating that these constructs are best

conceptualized as statistically interconnected components of adult learning rather than isolated educational processes. Previous research has generally examined the relationship from a single directional perspective, focusing either on the influence of workplace learning on adult skills (Billett, 2001; Eraut, 2004) or on how individuals with stronger cognitive skills are more likely to participate in learning-intensive work environments (OECD, 2019; Desjardins, 2017). By systematically comparing multiple competing SEM specifications, the present study extends this literature by showing that the relationship remains evident across alternative theoretical and statistical assumptions.

Second, this study contributes methodologically by demonstrating the value of comparative structural equation modeling for evaluating competing theoretical explanations. Rather than relying on a single structural model, the study compared forward recursive, reverse recursive, correlated-disturbance, reciprocal, refined latent, and instrumental-variable specifications. This comparative approach provides a more comprehensive understanding of the WBL–ACD relationship while highlighting the importance of evaluating model assumptions before drawing substantive conclusions. The findings suggest that convergence across multiple models offers stronger evidence than reliance on a single statistically significant specification.

Third, this dissertation introduces an SEM-informed static policy optimization framework that bridges explanatory modeling and decision support. Whereas previous studies have primarily focused on explaining workplace learning outcomes, the present study demonstrates how structural relationships can inform evidence-based workplace-learning recommendations. By integrating SEM with static policy optimization and bootstrap validation, the study illustrates how explanatory statistical models can be translated into practical decision-support tools while

remaining grounded in observed data. This methodological integration represents an important contribution to adult education, workforce development, and evaluation research.

Fourth, the findings have important implications for employers, workforce-development professionals, educators, and policymakers. The results suggest that organizations should move beyond one-size-fits-all workplace-learning programs. The SEM-informed static policy optimization demonstrated that the effectiveness of workplace-learning strategies depends on employees' existing WBL–ACD profiles. Consequently, organizations may achieve better learning outcomes by aligning workplace-learning opportunities with employees' cognitive characteristics rather than implementing identical learning interventions across the workforce.

Additionally, the findings highlight the importance of creating workplaces that encourage active participation in organizational improvement. The mediation analyses suggest that opportunities to contribute to improving work organization and work processes constitute one pathway through which workplace learning is associated with adult cognitive development. Organizations should therefore complement formal training with opportunities for collaborative problem solving, process improvement, and employee participation in workplace innovation.

Moreover, the optimization results provide practical guidance for workforce-learning design. Digital learning emerged as the preferred strategy for individuals with high workplace-learning engagement and cognitive proficiency, whereas structured training and collaborative workplace learning were more frequently recommended for intermediate cognitive states. These findings suggest that organizations should adopt adaptive workplace-learning strategies that reflect employees' existing learning needs and developmental trajectories.

Finally, the study has implications for workforce-development policy. National and organizational initiatives frequently emphasize expanding access to workplace learning without

considering whether different learning strategies may be appropriate for different groups of workers. The present findings suggest that evidence-informed workplace-learning policies should emphasize targeted and adaptive learning opportunities rather than universal interventions, thereby supporting more efficient investment in workforce development.

Future Research

Several opportunities exist for extending the present research. First, future studies should employ longitudinal data to examine how workplace learning and adult cognitive development evolve over time and to evaluate reciprocal relationships using temporal rather than cross-sectional evidence. Such designs would strengthen causal inference and permit the direct examination of developmental pathways.

Second, the SEM-informed static policy optimization framework should be evaluated across additional countries participating in PIAAC. Cross-national analyses would allow researchers to examine whether optimal workplace-learning strategies differ across labor-market structures, educational systems, and organizational cultures.

Third, future research should investigate additional organizational mechanisms that may explain the relationship between workplace learning and adult cognitive development, including job autonomy, leadership, organizational climate, psychological safety, and employee motivation. Expanding the theoretical model may provide a more comprehensive understanding of the workplace conditions that facilitate adult learning.

Finally, future methodological research could extend the present framework by integrating longitudinal SEM with dynamic reinforcement learning or other sequential decision-making approaches. Such approaches would enable researchers to estimate adaptive workplace-

learning policies that evolve over time as employees' cognitive development changes, thereby extending the present static optimization framework toward dynamic learning systems.

Concluding Discussion

This study examined the relationship between work-based learning and adult cognitive development using nationally representative PIAAC 2023 data and an integrated analytical framework combining structural equation modeling and SEM-informed static policy optimization. The findings demonstrated that work-based learning and adult cognitive development are closely interconnected across literacy, numeracy, and adaptive problem solving. Rather than supporting a single directional explanation, the comparative SEM analyses indicated that the relationship is best understood as one of robust statistical interdependence, with evidence converging across multiple complementary model specifications.

Building upon these structural findings, the SEM-informed static policy optimization demonstrated that no single workplace-learning strategy is universally optimal. Instead, the effectiveness of workplace-learning interventions depends on individuals' existing WBL–ACD profiles. Digital learning consistently emerged as the preferred strategy for individuals with high workplace-learning engagement and cognitive proficiency, whereas structured training and collaborative workplace learning were more frequently recommended for intermediate states. Bootstrap analyses further showed that recommendations for high-performing states were highly stable, while intermediate states exhibited greater uncertainty because several workplace-learning strategies produced comparable expected rewards.

Collectively, this study advances both theory and practice by moving beyond the traditional question of whether workplace learning and adult cognitive development are related

to examining how that relationship can inform evidence-based workplace-learning decisions. By integrating comparative SEM, mediation analysis, robustness assessment, and SEM-informed static policy optimization, the dissertation demonstrates that explanatory statistical models can be translated into practical decision-support frameworks. Ultimately, the proposed WBL–ACD framework provides a foundation for designing more adaptive, evidence-informed workplace-learning systems that recognize the diversity of adult learners and the importance of aligning learning opportunities with employees' cognitive profiles.

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