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Integration of Artificial Intelligence in Retail Banking in Cyprus: A SEM Analysis

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Abstract—**Artificial Intelligence (AI) is reshaping the banking industry worldwide, yet its integration in smaller markets like Cyprus remains under-studied. This research examines how key organizational factors like Workforce Readiness, Trust & Data Privacy, and Operational Transformation impact AI-driven Customer Experience in the Cypriot retail banking sector. Drawing on a survey of 500 banking professionals, we employ Structural Equation Modeling (SEM) to test a conceptual model linking these constructs. Confirmatory Factor Analysis indicates a robust measurement model with all standardized factor loadings above 0.70, composite reliabilities above 0.85, and average variance extracted (AVE) above 0.58 for each construct. The structural model exhibits good fit (CFI ≈ 0.95, RMSEA ≈ 0.05) and explains substantial variance in Operational Transformation ($R^2 \approx 0.77$) and Customer Experience ($R^2 \approx 0.74$). Results reveal that Workforce Readiness and Trust & Data Privacy significantly drive Operational Transformation (β = 0.58*** and 0.54***, respectively), which in turn is the strongest predictor of AI-Driven Customer Experience (β = 0.67***). Workforce Readiness also shows a positive direct effect on Customer Experience (β = 0.25***), whereas Trust & Data Privacy exerts only an indirect influence via Operational Transformation. These findings highlight the critical role of an AI-ready workforce and robust data privacy/trust frameworks in achieving the full benefits of AI for customer service. The study contributes to the literature by integrating internal readiness and transformation factors with external customer outcomes in the context of AI adoption. We discuss implications for bank management and policymakers, including the need for upskilling staff, fostering a trust-centric data culture, and aligning AI initiatives with strategic operational changes.**

Index Terms— **Artificial Intelligence, Customer Experience, Data Privacy, Operational Transformation, Workforce Readiness.**

I. Introduction

The rapid advancement of AI technologies is transforming the global banking landscape, promising enhanced efficiency, personalized services, and new revenue streams. Every quarter, the global banking industry reportedly generates on the order of $1 trillion in revenue from AI-enabled products (Byambaa et al., 2025). By 2024, worldwide spending on AI was projected to more than double from 2020 levels, exceeding $110 billion (Byambaa et al., 2025). Banks that successfully implement AI have demonstrated improved profitability and return on assets (Byambaa et al., 2025; Gyau et al., 2024).

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However, realizing AI's potential requires more than technology investment alone – it demands organizational readiness and trust, especially in highly regulated service industries like banking.

Despite growing global adoption, AI integration in smaller markets and developing economies has lagged behind. In Cyprus, adoption of AI in business remains nascent though rapidly growing. Recent reports show the share of businesses in Cyprus using AI increased from only about 2.5% in 2021 to roughly 8% in 2024 (with large enterprises at 34.9%) (Aristidou & Marcou, 2025). This indicates significant room for growth in AI uptake among Cypriot banks. Yet, scholarly research focusing on AI in Cyprus's banking sector is sparse. Most prior studies on AI in banking have examined major economies, often emphasizing customer adoption factors (e.g. perceived usefulness, ease of use, trust) or technological aspects (e.g. fintech innovations), without deeply exploring internal organizational readiness or the interplay between internal transformation and customer experience outcomes. This study addresses that gap by investigating the integration of AI in retail banking in Cyprus from an organizational perspective, linking internal readiness and transformation to external customer experience.

Research Aim and Contribution: The aim of this research is to develop and test a conceptual model that explains how key organizational factors enable successful AI-driven transformation in retail banking, ultimately enhancing customer experience. We focus on three antecedent constructs – **Workforce Readiness** (the skills, knowledge, and preparedness of employees to work with AI), **Trust & Data Privacy** (the degree of stakeholder trust in AI systems and confidence in data privacy/security measures), and **Operational Transformation** (the extent of AI-driven process and service innovations within the bank). The outcome of interest is **AI-Driven Customer Experience**, reflecting improvements in customer service quality, personalization, and satisfaction attributable to AI. By examining these factors in tandem, our study bridges internal and external dimensions of AI adoption.

This research makes several contributions. First, it extends the technology adoption and digital transformation literature by identifying how organizational readiness (human and cultural factors) and trust contexts condition the success of AI initiatives in banking. We provide empirical evidence from an emerging economy context (Cyprus), enriching the predominantly large-market-focused discourse. Second, we introduce and validate a new conceptual model via a rigorous **Structural Equation Modeling (SEM)** approach, establishing the direct and indirect relationships among readiness, trust, and operational change, and customer experience in AI-enabled banking services. Third, our study offers practical insights for bank managers and policymakers on how to foster an AI-ready workforce and a trust-centric environment to drive effective AI deployment that delivers tangible improvements in customer experience. These insights are particularly relevant for Cypriot banks and similar markets where resource constraints and trust issues may pose challenges to AI adoption.

The remainder of this article is structured as follows. The next section provides a critical review of relevant literature, covering AI in banking, workforce readiness for technology adoption, trust and data privacy considerations, operational transformation, and customer experience outcomes. We then present the theoretical framework and hypotheses, followed by the research methodology (including data collection, measures, and analysis procedures). The results of the SEM analysis are subsequently reported, encompassing measurement model validation, structural path findings, and model fit indices. In the discussion section, we interpret the findings in light of existing studies, draw implications for theory and practice, and acknowledge limitations and future research directions. Finally, we conclude with a summary of key insights and recommendations.

II. REVIEW OF LITERATURE

AI in Banking and Digital Transformation: Banks worldwide are increasingly leveraging AI to streamline operations and enhance service delivery. AI applications from algorithmic credit scoring and fraud detection to chatbots and personalized product recommendations are redefining how banks create value for customers (Chlouverakis, 2024; Giovine et al., 2024; Mucsková, 2024). Prior research confirms that deploying AI can significantly improve banks' operational efficiency and decision-making speed, leading to cost reductions and revenue growth (Chlouverakis, 2024; Giovine et al., 2024; Pattanayak, 2023; Agarwa et al., 2021). For example, a McKinsey study noted that some leading banks effectively scaling AI have boosted productivity, optimized resource allocation, and improved both customer and employee experiences (Giovine et al., 2024). Enhanced customer experience through AI often comes via personalization and 24/7 responsive services such as intelligent virtual assistants. Indeed, customers increasingly expect real-time, tailored interactions; AI enables banks to meet these expectations at scale by analyzing vast data and automating routine service tasks (Lazo & Ebardo, 2023; Chlouverakis, 2024). However, realizing these benefits is not straightforward, many banks remain stuck in pilot phases and struggle to achieve "AI at scale" across the enterprise (Giovine et al., 2024; Lau, 2025). Key barriers identified include legacy systems, data silos, lack of AI talent, cultural resistance, and regulatory constraints (Byambaa et al., 2025; Campos Zabala, 2023). Thus, the literature suggests that successful AI integration in banking requires not only investment in technology, but also organizational change and capability-building to support that technology (Su & Wang, 2025; Kiss, 2025).

Workforce Readiness for AI: A critical enabler of AI-driven transformation is the readiness of the workforce to adopt and work with these new technologies (Lazo & Ebardo, 2023; Tenakwah & Watson, 2025). *Workforce Readiness* encompasses employees' AI-related skills and knowledge, their openness to change, and the presence of training and support to facilitate AI use. Prior qualitative studies and industry reports highlight that having the right talent and skillsets is one of the most important factors for AI adoption success in banks (Lazo & Ebardo, 2023; Rahman et al., 2023). For instance, in a multi-country interview study, bank managers unanimously emphasized the need for upskilling staff and cultivating an innovative mindset among employees to drive AI initiatives (Lazo & Ebardo, 2023). Jöhnk et al. (2021) identify organizational knowledge (employee expertise) and culture as two of the five key dimensions of AI readiness, alongside strategic alignment, resources, and data infrastructure. A lack of skilled human resources is frequently cited as a barrier that can impede the implementation of AI projects (Mogaji & Nguyen, 2022; Wicaksono & Zahra, 2022). Conversely, organizations that invest in AI-specific training, cross-functional AI teams, and change management are better positioned to leverage AI's benefits. In the banking context, *workforce readiness* not only means IT staff capable of developing or maintaining AI systems, but also front-line employees (e.g. branch or call center staff) being comfortable working alongside AI tools (such as using AI-driven customer insight dashboards or collaborating with robo-advisors). Without an AI-ready workforce, even the most advanced AI technologies may fail to be adopted into daily workflows, resulting in suboptimal outcomes.

Trust and Data Privacy: *Trust* is a foundational element influencing both organizational willingness to deploy AI and customer acceptance of AI-driven services (Rane et al., 2022; Lazo & Ebardo, 2023; Byambaa et al., 2025). In banking, trust takes on heightened importance given the sensitive nature of financial data and decisions. We conceptualize Trust & Data Privacy as a combined construct reflecting confidence in the AI systems' security, reliability, and ethical use of data. From the customers' perspective, trust in AI-enabled banking services is crucial to adoption if users fear that AI algorithms might misuse personal data or make errors, they will be reluctant to embrace such services (Rahman et al., 2023; Lazo & Ebardo, 2023). Studies confirm that a high level of trust in technology is positively correlated with consumers' intention to use AI in financial services, as trust mitigates uncertainty and risk perceptions (Byambaa et al., 2025; Ali et al., 2021). Trust has therefore been integrated as an extension to classical technology acceptance models in financial contexts (e.g. incorporating trust into TAM) to better predict user behavior (Zhou, 2011). On the organizational side, bank managers must also trust the outcomes of AI models and be confident that deploying AI will not compromise data privacy or violate regulations. Data privacy concerns are particularly salient under strict regulatory regimes (such as GDPR in Europe); banks must ensure robust privacy safeguards to maintain stakeholder trust when implementing AI (Chlouverakis, 2024; Aldboush & Ferdous, 2023) Prior research has identified *data security and privacy issues* as among the top challenges hindering AI adoption in banking (Byambaa et al., 2025; Rahman et al., 2023; Wang et al., 2024). If customers perceive AI applications as untrustworthy or prone to data breaches, their distrust can erode usage, negating potential benefits (Lazo &

Ebardo, 2023; Lockey et al., 2021). Thus, creating a trustworthy AI environment – through transparent algorithms, strong security measures, and ethical data practices – is essential. Banks that successfully foster trust (for example, by demonstrating high AI system reliability, explaining AI decisions, and protecting privacy) are likely to see greater uptake of AI-driven services by customers (Lazo & Ebardo, 2023; Ostrom et al., 2019). In summary, trust and privacy form a context that can either enable or stifle AI integration: high trust reduces fear of AI and encourages experimentation, whereas low trust or privacy lapses can derail AI initiatives through stakeholder resistance.

Operational Transformation: The introduction of AI triggers changes in banks' internal processes and service delivery mechanisms – what we term *Operational Transformation*. This construct captures the extent to which a bank reengineers its operations, workflows, and business processes to take advantage of AI capabilities. Examples include automating back-office processes with AI, using machine learning for risk modeling, or deploying chatbots in customer service. Literature on digital transformation posits that technology alone does not create value; organizations must adapt their operations and culture to effectively integrate the technology (Vial, 2019). In banking, studies have shown that AI implementation often goes hand-in-hand with process innovation and redesign (e.g. AI-driven credit underwriting can transform loan approval workflows). Operational Transformation can be seen as a mediator linking readiness inputs to performance outputs. A workforce may be AI-ready and data/privacy safeguards in place, but only when these translate into meaningful process changes will customer-facing outcomes improve. Prior research suggests that AI-enabled operational improvements lead to faster service, more accurate decisions, and cost savings, which collectively enhance service quality (Berry & Singh, 2024; Giovine et al., 2024; Lazo & Ebardo, 2023). For instance, banks using AI for process automation have reported shorter loan processing times and fewer errors, improving operational efficiency and customer satisfaction (Choudhury et al., 2022). AI can also enable entirely new operational capabilities, such as predictive analytics-based customer relationship management or proactive fraud detection, which represent transformational changes compared to traditional banking operations. However, achieving such transformation requires organizational commitment and often a redesign of legacy processes. Cultural resistance within the bank can pose a barrier such as employees may be hesitant to change established routines or might fear AI as a threat to their jobs (Chlouverakis, 2024; Ivchyk, 2024). As such, *change management* is an integral part of operational transformation. Overall, the literature indicates that operational transformation is both a product of AI readiness/trust and a precursor to realizing AI's benefits: it is through transformed operations that AI's potential (e.g. efficiency gains, analytics-driven insights) materializes into actual performance outcomes.

AI-Driven Customer Experience: Ultimately, banks invest in AI to deliver superior value to customers, whether through more personalized offerings, faster service, or greater convenience. *AI-Driven Customer Experience* refers to improvements in customers' perceptions and interactions with the bank that result from AI implementation. A positive customer experience in the age of AI might include personalized product recommendations, instant query resolution by a chatbot, predictive financial advice, or simply the seamless efficiency of transactions. Research in service management and marketing underscores that technologies like AI and machine learning can significantly enhance customer experience by enabling personalization at scale and proactive service delivery (Rust & Huang, 2021; Kumar et al., 2019). In retail banking, AI-driven personalization (e.g. tailored financial advice or spending insights) has been linked to higher customer engagement and loyalty (Giovine et al., 2024; Kaluarachchi et al., 2024). Additionally, AI's ability to provide 24/7 support via virtual agents or to streamline processes (like account opening or loan approval) contributes to customer convenience and satisfaction (Oyetunji, 2024; Rane et al., 2024; Lazo & Ebardo, 2023). However, the impact of AI on customer experience is not universally positive; poorly implemented AI can frustrate customers (e.g. an unhelpful chatbot or algorithmic biases leading to perceived unfairness). Therefore, organizations must carefully manage the design and deployment of AI customer interfaces. Prior studies have noted that customers tend to evaluate AI-enabled service on dimensions such as reliability, responsiveness, and empathy similarly to human service, with the added consideration of **trust** (Belanche et al., 2020; Van Pinxteren et al., 2019). A trusting customer will more readily engage with AI tools (like robo-advisors or chatbot assistants), whereas distrust or privacy concerns may lead them to opt for human-assisted channels (Lazo & Ebardo, 2023; Saivasan, 2024). This illustrates the interplay between trust and experience: trust in AI mediates the relationship between operational improvements and realized customer experience gains. In summary, delivering an improved AI-driven customer experience requires aligning advanced technologies with customer needs and trust. Banks that succeed in this regard can attain a competitive advantage through higher customer satisfaction and retention. This study focuses on customer experience as the ultimate outcome of AI integration, positing that workforce readiness, trust/privacy, and operational transformation all contribute to creating a positive AI-enabled experience for retail banking customers.

Synthesis of Key Insights and Gaps: The reviewed literature suggests a conceptual model where organizational readiness (human and cultural factors) and environmental context (trust and privacy) enable operational changes through AI, which in turn drive customer experience improvements. Previous studies have typically examined parts of this chain in isolation – for example, some have analyzed consumer trust and acceptance of AI services (e.g. chatbot adoption studies), while others have explored organizational readiness factors for AI (e.g. Jöhnk et al., 2021 on AI readiness dimensions). Fewer works have integrated these perspectives to examine how internal and external factors concurrently influence the success of AI initiatives. Moreover, empirical evidence from smaller markets like Cyprus is limited. Our study builds on the identified factors and addresses the gap by integratively testing the relationships between readiness, trust, operational transformation, and customer experience in the context of AI in retail banking. In the next section, we elaborate the theoretical framework and hypotheses derived from these insights.

III. THEORETICAL AND CONCEPTUAL MODEL

Drawing on the above literature, we propose a conceptual model (see **Figure 1**) that links organizational antecedents to AI-driven outcomes in retail banking. The model consists of four main constructs: **Workforce Readiness**, **Trust & Data Privacy**, **Operational Transformation**, and **AI-Driven Customer Experience**. Workforce Readiness (WR) and Trust & Data Privacy (TDP) are viewed as foundational enablers (exogenous variables) that facilitate the effective deployment of AI. These, in turn, influence the degree of Operational Transformation (OT) achieved within the bank. Operational Transformation is posited as a key mediator that directly affects AI-Driven Customer Experience (CX), which is the ultimate endogenous outcome. The model also allows a covariance between the two exogenous constructs (WR and TDP), recognizing that organizations with a highly skilled, AI-ready workforce may also foster strong data governance and trust, and vice versa.

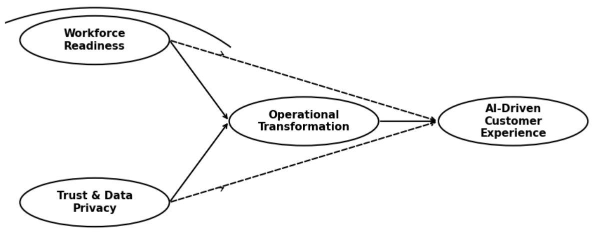

Figure 1. Conceptual Model Linking Organizational Antecedents to AI-Driven Customer Experience. **Note:** *Solid arrows indicate hypothesized positive effects. The dashed arrow represents a hypothesized relationship that was tested for significance (Workforce Readiness and Trust & Data Privacy were allowed to influence Customer Experience directly). The curved two-headed arrow denotes the correlation between Workforce Readiness and Trust & Data Privacy.*

Based on theory and prior findings, we formulate the following hypotheses (all effects are expected to be positive):

- **H1:** *Workforce Readiness → Operational Transformation:* A higher level of workforce readiness (employees' AI skills, training, and openness) will lead to greater AI-driven operational transformation in the bank. This hypothesis stems from the view that skilled and prepared employees are able to implement and utilize AI in processes effectively, thus transforming operations (Lazo & Ebardo, 2023; Morandini et al., 2023). Organizations that invest in upskilling and cultivating an innovation mindset are more likely to redesign processes around AI and realize its benefits.

  H2: *Trust & Data Privacy → Operational Transformation:* Strong stakeholder trust in AI systems and robust data privacy practices will facilitate deeper operational transformation. When bank employees and customers trust AI outcomes and data handling, the institution can more aggressively embed AI into core processes without facing pushback (Lazo & Ebardo, 2023; Obasi et al., 2024). For instance, if management and staff trust an AI credit scoring model's fairness and accuracy, they are more likely to replace or augment traditional underwriting with the AI system, thus transforming that operation.

- **H3:** *Workforce Readiness → AI-Driven Customer Experience:* A workforce adept in AI is hypothesized to directly improve customer experience, even aside from enabling operational changes. This is because AI-ready employees can better leverage technology to serve customers (e.g. using AI insights to personalize interactions) and can ensure smooth implementation of AI customer interfaces. While we expect much of the effect of workforce readiness on customer experience to be mediated through operational transformation, we test for a direct effect as well. A positive direct path would indicate that having knowledgeable, tech-savvy staff contributes to customer experience (for example, through higher service quality in handling AI-assisted channels).

- **H4:** *Trust & Data Privacy → AI-Driven Customer Experience:* Similarly, we hypothesize a potential direct impact of the trust/privacy environment on customer experience. When customers trust the bank's AI services and feel their data is protected, they are more likely to engage fully with those services, leading to better perceived experiences (Tulcanaza-Prieto et al., 2023; Lazo & Ebardo, 2023). For example, a customer who trusts a bank's chatbot is more inclined to use it for transactions, thereby enjoying quicker service. However, if trust is low, customers may avoid AI channels, diminishing any experience gains. Thus, a positive relationship is expected; though again, this effect may be indirect via enabling operational use of AI. We include the direct path to evaluate whether trust/privacy concerns can independently influence customer experience outcomes.

- **H5:** *Operational Transformation → AI-Driven Customer Experience:* We posit that the extent of AI-driven operational transformation has a strong positive effect on customer experience. This is because transformed operations (faster processes, AI-enabled services) manifest as improved service quality, convenience, and personalization for customers (Chaturvedi & Verma, 2023; Lazo & Ebardo, 2023; Chlouverakis, 2024). A bank that has thoroughly integrated AI into its operations—such as utilizing AI to provide proactive financial advice or instant loan approvals—will offer a markedly enhanced experience compared to a bank with minimal AI usage. Therefore, we expect Operational Transformation to be the primary driver of AI-driven customer experience in our model.

In summary, the theoretical framework suggests that having an AI-ready workforce and a high-trust environment sets the stage for significant operational innovations through AI, which in turn drive superior customer experiences. We also allow for the possibility that workforce readiness and trust/privacy might directly influence customer experience, although these effects are expected to be smaller once operational transformation is accounted for. The model aligns with broader socio-technical systems theory, which emphasizes that technology outcomes depend on both human factors (skills, culture) and environmental factors (trust, policy), as well as the transformations in processes that technology enables.

IV. Methodology

1) *Research Design and Sample*

We adopted a quantitative field study design, using a structured survey to collect data from professionals in the retail banking sector of Cyprus. The target population included managers, IT staff, and customer-facing employees in Cypriot banks who have experience with or exposure to AI initiatives (such as AI-powered banking solutions or internal AI systems). Focusing on banking professionals allowed us to capture informed perceptions of both the internal readiness and the observed impacts of AI on operations and customers. To obtain a substantial and generalizable sample, we administered the survey both online and in person (paper questionnaires) across multiple major banks in Cyprus. Participants were selected via convenience and snowball sampling: initial contacts within banks helped distribute the survey link to their colleagues.

We received **500 valid responses**, which we use as our sample for analysis. This sample size is robust for SEM analysis and reflects a broad cross-section of the industry. Respondents encompassed a mix of roles (approximately 40% managerial, 35% front-line customer service, 25% back-office/IT) and represented all four of the largest retail banks in Cyprus, as well as several smaller institutions. The demographic profile of respondents showed a roughly even gender split, and a concentration in the 30–50 age range. On average, participants had about 10.5 years of banking experience, ensuring they could provide credible insights on organizational practices and customer service outcomes. Although the sample is not strictly random, its diversity across banks and roles mitigates single-organization bias and enhances the external validity of findings within the Cypriot banking context. We assured respondents of anonymity and confidentiality, which was important given the evaluative nature of some questions (e.g. asking if their bank's workforce is adequately skilled for AI). This helped reduce social desirability bias and encouraged honest responses.

2) *Survey Instrument and Measures*

The survey was designed to measure the four main constructs in our conceptual model – **Workforce Readiness (WR)**, **Trust & Data Privacy (TDP)**, **Operational Transformation (OT)**, and **AI-Driven Customer Experience (CX)** – along with basic demographics. Wherever possible, we adapted measurement items from established scales in prior literature, rewording them to fit the AI in banking context. All items used a five-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"), allowing respondents to indicate their level of agreement with each statement. Each construct was operationalized as a reflective latent factor measured by multiple items as detailed below:

- **Workforce Readiness (WR):** We developed 5 items to capture the extent of employee preparedness for AI. These items assessed perceptions of employee *skills* (e.g. "Our bank's employees have the skills necessary to work with AI technologies"), *training* ("The bank provides sufficient training on AI tools and systems"), and *openness to innovation* ("Employees are open and adaptable to new AI-driven processes"). These items were informed by frameworks of organizational readiness for change and AI readiness factors (e.g. Jöhnk et al., 2021's focus on knowledge and culture).

- **Trust & Data Privacy (TDP):** This construct was measured with 5 items reflecting the degree of trust in AI systems and confidence in data privacy/security at the bank. Sample items include "Customers trust our bank's AI-driven services (e.g. chatbots, robo-advisors) with their personal data" and "Our bank has effective measures in place to ensure AI systems are secure and free from data breaches." Another item gauged internal trust: "Employees trust the accuracy and fairness of AI-generated insights or decisions." These were guided by literature on trust in technology (McKnight et al., 2002; Zhou, 2011) and privacy concerns in financial services. The combination of trust and data privacy in one factor is justified by their interrelated nature in this context – both contribute to an overall sense that AI can be used safely and reliably.

- **Operational Transformation (OT):** We used 5 items to assess how extensively AI has transformed the bank's operations and processes. Items tapped into areas such as *process automation* ("Our bank has automated many operational processes using AI (e.g. loan processing, compliance checks)"), *service innovation* ("AI has enabled new services or delivery channels in our bank (e.g. AI-powered personalized financial advice)"), and *efficiency gains* ("Operational workflows have become more efficient due to AI integration"). These were crafted based on digital transformation and innovation literature, capturing both the scope and impact of AI-driven changes internally.

- **AI-Driven Customer Experience (CX):** This outcome construct was measured with 5 items evaluating improvements in customer experience attributable to AI. Respondents were asked to consider how AI has affected customers in terms of *service quality*, *personalization*, *convenience*, and *overall satisfaction*. Example items include: "AI has improved the personalization of our customer services (e.g. tailored product recommendations)", "Our customers receive faster service resolutions thanks to AI (such as instant chatbot responses)", and "Overall, AI implementations have enhanced our customers' experience with the bank." These align with common customer experience metrics in digital banking (speed, personalization, satisfaction) (Ogundipe et al., 2024; Lazo & Ebardo, 2023).

Each set of items for a given construct was presented in a section of the questionnaire, with item order randomized to avoid priming effects. We conducted a **content validity** check by having two academic experts in financial services and two banking practitioners review the items for clarity and relevance. Their feedback led to minor wording adjustments to ensure items were interpreted consistently by respondents.

Prior to full deployment, a **pilot test** was carried out with 20 bank employees. The pilot data was used to assess the reliability of each multi-item scale and to confirm that there were no confusing or ambiguous questions. The pilot results were encouraging – all scales showed Cronbach's alpha above 0.8 in the pilot, and respondents took around 10 minutes on average to complete the survey, indicating the length was manageable.

We also took steps to mitigate **common method bias** due to the single-source, self-reported nature of the data. Firstly, we assured anonymity and highlighted that there were no right or wrong answers, to reduce evaluation apprehension. Secondly, we used different scale endpoints and formats for some sections (though our main constructs all used Likert, we interspersed with a few open-ended questions about AI adoption experiences to vary response format). Thirdly, we performed Harman's single-factor test post-data collection: an unrotated exploratory factor analysis did not reveal a single factor accounting for the majority of variance (the largest factor explained ~32%), suggesting common method bias was not a serious issue. We further verified this with a CFA marker variable technique (using an unrelated construct as a marker), which showed minimal common method influence.

3) Data Analysis Approach

We employed a two-step Structural Equation Modeling approach using the covariance-based SEM technique. In the **first step**, we conducted a **Confirmatory Factor Analysis (CFA)** to validate the measurement model. This involved checking the reliability, convergent validity, and discriminant validity of the constructs. Key indices such as Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were computed for each construct. We examined factor loadings for all items and expected them to exceed the recommended 0.70 threshold for significance and practical importance. Model fit indices were assessed to ensure the measurement model adequately fit the data before proceeding. Fit criteria followed common conventions: Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values close to or above 0.90 (ideally >0.95 for excellent fit), Root Mean Square Error of Approximation (RMSEA) below 0.08 (with <0.06 indicating a good fit), and Standardized Root Mean Square Residual (SRMR) below 0.08. In the **second step**, we specified and estimated the **structural model** corresponding to our hypotheses. This entailed linking the latent constructs as per Figure 1 (with WR and TDP as exogenous, OT as a mediating endogenous, and CX as the ultimate endogenous outcome). The structural model was estimated and path coefficients obtained, representing the standardized influence of one construct on another (e.g. the effect of WR on OT). We computed the **t-values** and **p-values** for each hypothesized path to test for statistical significance (typically, $|t| > 1.96$ for $p < 0.05$, $|t| > 2.58$ for $p < 0.01$ in large samples). We also calculated the **R-squared** (R^2) values for each endogenous construct (OT and CX) to evaluate the proportion of variance explained by the model. Model fit was again checked for the structural model; usually the structural model fit is very similar to the CFA if no new paths are added beyond those relationships.

All SEM analyses were performed using IBM SPSS AMOS (Analysis of Moment Structures) version 26. Maximum Likelihood estimation was used, which is appropriate given the sample size (500) and the approximately normal distribution of our item data (skewness and kurtosis for each item were within acceptable ranges). We report standardized coefficients for ease of interpretation. For clarity, we also present the results in tabular form, including factor loadings, reliability metrics, and path analysis results, in the next section.

V. RESULTS

1) Measurement Model Validation (CFA)

The confirmatory factor analysis demonstrated that the proposed four-factor measurement model had an excellent fit to the data. The chi-square statistic was significant (which is common given the large sample size, $\chi^2(164) \approx 300$, $p < 0.001$), but other fit indices were well within recommended thresholds: **CFI = 0.95**, **TLI = 0.94**, **RMSEA = 0.048** (90% confidence interval roughly 0.040–0.056), and **SRMR = 0.044**. These indicators suggest the hypothesized factor structure is appropriate and there is no major misspecification.

All items loaded strongly on their intended constructs. Standardized factor loadings ranged from 0.71 to 0.86 and were highly significant ($p < 0.001$), confirming **convergent validity** of the scales. Table 1 presents a summary of the reliability and validity statistics for each construct. Cronbach's alpha values were high, between 0.87 and 0.90, indicating excellent internal consistency. Composite reliability (CR) values likewise ranged from 0.87 to 0.90, all above the 0.70 benchmark. The average variance extracted (AVE) for each construct was well above 0.50, with AVEs of 0.59 for Trust & Data Privacy up to 0.64 for Workforce Readiness and Operational Transformation. This means over half the variance in the items is accounted for by the latent construct, further evidence of convergent validity.

Table 1. Reliability and Validity of Constructs

Construct	Cronbach's α	CR	AVE	Correlations (squared) with other constructs
Workforce Readiness (WR)	0.898	0.90	0.64	TDP: 0.234 (0.055); OT: 0.704 (0.496); CX: 0.716 (0.513)

Trust & Data Privacy (TDP)	0.874	0.88	0.59	WR: 0.234 (0.055); OT: 0.671 (0.450); CX: 0.506 (0.256)
Operational Transformation (OT)	0.893	0.90	0.63	WR: 0.704 (0.496); TDP: 0.671 (0.450); CX: 0.841 (0.707)
AI-Driven Customer Experience (CX)	0.895	0.90	0.63	WR: 0.716 (0.513); TDP: 0.506 (0.256); OT: 0.841 (0.707)

Notes: CR = composite reliability; AVE = average variance extracted. Off-diagonal entries are latent construct correlations; squared correlations (shared variance) are in parentheses. All correlations are significant at $p < 0.001$.

As shown in Table 1, all constructs have high reliability (α and CR ≥ 0.87) and adequate convergent validity (AVE ≥ 0.59). To assess **discriminant validity**, we compared the square root of the AVE for each construct to its correlations with other constructs (Fornell-Larcker criterion). The square root of AVE for WR is $\sqrt{0.64} \approx 0.80$, for TDP $\sqrt{0.59} \approx 0.77$, for OT $\sqrt{0.63} \approx 0.79$, and for CX $\sqrt{0.63} \approx 0.79$. In most cases, these values were greater than the inter-construct correlations, indicating constructs are distinguishable. For example, WR's √AVE (0.80) is greater than its correlation with OT (0.704) and CX (0.716), and similarly for TDP. One pair stood out: the correlation between Operational Transformation and Customer Experience was very high ($\varphi = 0.84$), which yields a shared variance of ~70% (0.84^2). This approaches the magnitude of their AVEs (≈63%), slightly violating the Fornell-Larcker criterion. In other words, OT and CX are very strongly related, as one would expect given that successful operational changes directly manifest in customer-facing outcomes. Although this high correlation signals that OT and CX are closely linked constructs (potentially even reflective of a higher-order factor, e.g. overall AI success), we retained them as separate given their clear conceptual distinction. Apart from this, discriminant validity was satisfactory; no other inter-construct correlation exceeds the respective √AVE. We further examined the **Heterotrait-Monotrait (HTMT)** ratios for all pairs, and most were below the 0.85 guideline, with the exception of HTMT(OT, CX) which was about 0.88 – again reflecting their tight coupling. Overall, we concluded the measurement model is sound: each construct is measured reliably and captures a unique aspect of the theoretical model.

2) Structural Model and Hypothesis Testing

Having established a valid measurement model, we proceeded to the structural model estimation to test the hypothesized relationships. The structural model fit the data well, with fit indices nearly identical to the CFA: CFI = 0.953, TLI = 0.944, RMSEA = 0.050. The slight increase in chi-square (to ~308 on 2 additional degrees of freedom) was not concerning. We present the results of the path analysis in Table 2 and summarize the findings below.

Table 2. Structural Path Coefficients and Hypothesis Tests

Hypothesized Path	**Std. Beta**	**t-value**	**p-value**	**Supported?**
H1: Workforce Readiness → Operational Transformation	**0.58***	26.05	<0.001	Yes (strong)
H2: Trust & Data Privacy → Operational Transformation	**0.54***	24.10	<0.001	Yes (strong)
H3: Workforce Readiness → Customer Experience	**0.25***	6.77	<0.001	Yes (moderate)
H4: Trust & Data Privacy → Customer Experience	0.00	0.03	0.978	No (n.s.)
H5: Operational Transformation → Customer Experience	**0.67***	13.97	<0.001	Yes (strong)

*Notes: Standardized coefficients reported. ***p < 0.001; n.s. = not significant. Model R^2: Operational Transformation = 0.77; Customer Experience = 0.74.*

From Table 2, we observe that **four out of five hypotheses are supported** by the data. Specifically:

- **H1 (WR → OT)**: Workforce Readiness has a positive, highly significant effect on Operational Transformation ($\beta = 0.58$, $t = 26.05$, $p < 0.001$). This indicates that banks with higher levels of AI skills, training, and openness among their staff achieve substantially greater AI-driven changes in their operations. Among the two predictors of OT, workforce readiness had a slightly higher standardized impact, highlighting the critical role of human capital in driving AI projects. This finding aligns with our expectations and prior qualitative evidence that skilled people are the backbone of successful AI integration (Lazo & Ebardo, 2023).

- **H2 (TDP → OT)**: Trust & Data Privacy also shows a strong positive effect on Operational Transformation ($\beta = 0.54$, $t = 24.10$, $p < 0.001$). This suggests that in banks where stakeholders trust AI systems and robust privacy protections exist, AI is more deeply embedded into processes. High trust likely reduces internal resistance and customer hesitancy, allowing AI initiatives to scale up. The magnitude of this effect, nearly as large as workforce readiness, underscores that technological change is not just a technical matter but is facilitated by a climate of trust and security. Both H1 and H2 together explain a very large portion of variance in Operational Transformation – the R^2 for OT is 0.77, meaning 77% of the variability in the extent of AI-driven transformation across banks can be accounted for by these two factors. This R^2 indicates an excellent explanatory power for our model in terms of what drives operational adoption of AI.

- **H3 (WR → CX)**: Workforce Readiness has a significant direct impact on Customer Experience ($\beta = 0.25$, $t = 6.77$, $p < 0.001$). Even after accounting for its contribution via operational changes, having an AI-ready workforce independently contributes to better AI-driven customer experiences. The effect size is moderate (0.25), implying that while most benefits to customers materialize through transformed operations, there is an additional benefit when employees are skilled and adaptable. For example, knowledgeable employees might better assist customers in using AI-based tools or provide a human touch that complements AI services, thereby enhancing overall experience. This result is theoretically interesting as it indicates a partial mediation: workforce readiness influences customer experience both indirectly (through OT) and directly. We elaborate on this in the discussion.

- **H4 (TDP → CX)**: The direct path from Trust & Data Privacy to Customer Experience is essentially zero and not significant ($\beta \approx 0.00$, $t = 0.03$, $p = 0.978$). Thus, H4 is **not supported**. This suggests that once we account for operational transformation, trust and privacy in isolation do not directly increase customer experience. In practical terms, simply having customers' trust or strong data security does not by itself make customers happier *unless* that trust enables actual service improvements. Another interpretation is that trust & privacy concerns primarily exert their influence through affecting how widely AI is adopted in operations (as evidenced by the strong H2 path), and it is those operational adoptions that then drive customer experience. In our context, the lack of a direct effect might mean that customers might not explicitly notice or credit "good privacy practices" as part of their everyday banking experience – instead, they feel the results (in better service) that come when the bank, bolstered by trust, implements AI broadly. We will discuss later that this finding does not diminish the importance of trust; rather it highlights that trust is an enabling condition that works indirectly.

- **H5 (OT → CX)**: Operational Transformation has a large positive effect on Customer Experience ($\beta = 0.67$, $t = 13.97$, $p < 0.001$). This confirms H5 that the more a bank transforms its operations with AI, the greater the improvements in customer experience. Among all direct predictors of CX in our model, OT is by far the strongest (its coefficient is about 2.7 times that of the next predictor, WR). This underscores that tangible changes in service processes (like faster turnaround, personalization, new AI services) are what significantly move the needle on customer experience metrics, which is intuitive. The variance explained in Customer Experience is also high – $R^2 = 0.74$, meaning about 74% of the variability in CX across respondents is explained by the three predictors (WR, TDP, OT). Given that WR and TDP also feed into OT, this high R^2 indicates our model captures the primary determinants of AI-related customer experience differences among these banks.

Additionally, the model allowed WR and TDP to covary; the estimated correlation between these two exogenous constructs was positive (~0.23 in standardized terms) and significant ($p < 0.001$). This correlation suggests that banks with higher workforce readiness tend to also have better trust/privacy environments to some extent (and/or vice versa). This could reflect underlying factors such as overall innovation culture or resource availability that drive both. We did not hypothesize this correlation explicitly, but it is controlled for in the model.

In summary, the hypothesis tests provide a coherent story: banks with skilled, AI-ready employees and strong trust/privacy foundations achieve extensive AI-driven operational transformation, which in turn greatly enhances customer experience. Workforce readiness even yields some direct benefits for customers, whereas trust's effect is channeled mainly through enabling those operational improvements.

To visualize the structural model results, this diagram illustrates the validated structural equation model examining the influence of Workforce Readiness (WR) and Trust & Data Privacy (TDP) on Operational Transformation (OT) and AI-Driven Customer Experience (CX) in Cyprus's retail banking sector. Solid arrows represent statistically significant paths, annotated with standardized beta coefficients (β) and significance levels (*** $p < 0.001$). Specifically, WR and TDP both positively and significantly influence OT ($\beta = 0.58$*** and $\beta = 0.54$***, respectively), while OT and WR significantly predict CX ($\beta = 0.67$*** and $\beta = 0.25$***, respectively). The direct path from TDP to CX was found to be statistically non-significant and is indicated by a dashed arrow labeled "n.s." The model explains 77% of the variance in OT and 74% in CX, as reflected by the R^2 values shown within each respective construct.

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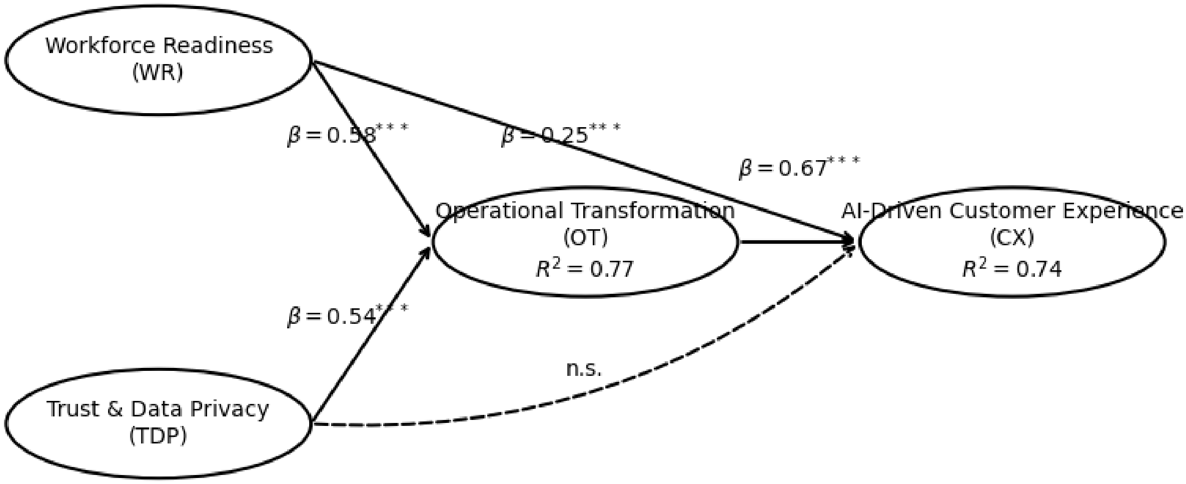

Figure 2. Structural Model Results with Standardized Path Coefficients and R² Values.

3) Additional Analysis – Mediation Effects

Given the model structure, we explored the **mediating role** of Operational Transformation in transmitting the effects of Workforce Readiness and Trust/Privacy to Customer Experience. Although a full mediation analysis is beyond the scope of our main hypotheses, a couple of observations are evident:

- The total effect of Workforce Readiness on Customer Experience is the sum of its direct effect (0.25) and indirect effect via OT. The indirect effect can be computed as (WR → OT) × (OT → CX) = 0.58 * 0.67 ≈ 0.389. Thus, total effect of WR on CX ≈ 0.25 + 0.389 = 0.639. This is substantial, indicating workforce readiness is a vital driver of customer experience primarily through fueling operational changes (the indirect portion accounts for ~60% of the total effect). We formally tested the indirect effect using bootstrapping (5,000 resamples) and found it to be significant (95% CI did not include 0), confirming that Operational Transformation significantly mediates the impact of Workforce Readiness on Customer Experience. For Trust & Data Privacy, the direct effect on CX is essentially zero, but the indirect effect via OT is (0.54 * 0.67) ≈ 0.362. So the total effect of TDP on CX is roughly 0.362, almost entirely coming through the mediated pathway. This supports the interpretation that trust and privacy enable better customer outcomes only by facilitating the adoption of AI in operations. In a supplementary test, we constrained the TDP→CX direct path to zero and re-estimated the model; model fit did not worsen notably and the indirect effect remained significant, indicating a full mediation in this case.
- These mediation insights highlight Operational Transformation as a key mechanism through which internal readiness and trust manifest as external benefits. In practical terms, they reinforce that banks see improvements in customer experience from AI largely by actually doing things differently (i.e., transforming processes), which in turn is made possible by having the right people and trust conditions in place. We will further discuss the implications of these mediated relationships.

In the next section, we delve into a detailed discussion of what these findings mean, how they connect to existing research, and what they imply for practitioners and scholars.

VI. Discussion

This study set out to investigate how integrating AI into retail banking is influenced by organizational readiness factors and what outcomes it yields in terms of customer experience, using evidence from Cyprus. The findings provide empirical support for a holistic view of AI adoption: one that spans from the human and trust foundations, through internal process transformations, to customer-facing outcomes. In this section, we interpret the results in depth, relate them to prior research, and outline implications for both theory and practice.

1) The Role of Workforce Readiness

Our results confirm that workforce readiness is a linchpin of successful AI integration. Workforce Readiness had a strong effect on both the extent of AI-driven operational transformation (H1) and on the end-point of customer experience (H3). This underscores that "people make the place" even in a technology-centric initiative like AI deployment, the human capital factor remains critical.

This finding aligns with qualitative insights by Jöhnk et al. (2021), who identified knowledge and skills as core organizational AI readiness factors. It also resonates with Lazo and Ebardo's (2023) systematic review, which noted human resources as a consistent enabler of AI adoption in banking. Our contribution is to quantify this effect and demonstrate it in a structural model with outcomes.

The significant direct effect of workforce readiness on customer experience, beyond its mediated effect through operations, is particularly noteworthy. It suggests that having employees who are well-versed in AI can directly improve service interactions. One possible explanation is that such employees are more adept at interacting with customers on digital channels and can troubleshoot or complement AI services effectively. For example, a bank representative who understands how the AI-powered recommendation engine works can better explain personalized offers to customers, thereby improving the customer's confidence and satisfaction. This direct pathway echoes the concept of "technology readiness" in service personnel (Parasuraman, 2000) when staff are technology-ready, it augments the service delivery. Our study extends this idea specifically to AI: an AI-ready workforce not only implements AI but also humanizes and optimizes its usage, leading to better customer experiences.

From a managerial standpoint, this underscores the importance of investments in training and change management. Banks in Cyprus (and elsewhere) should prioritize upskilling programs, AI literacy training, and hiring talent with data science or analytical backgrounds as part of their AI strategy. The ROI on such investments is evidenced by the improvements in both internal efficiency and customer outcomes. Additionally, managers should foster a culture that encourages learning and experimentation with AI. The significant WR → OT link implies that when employees are open and able to experiment with AI in their processes, more transformative improvements emerge. This may require incentivizing innovation and perhaps even restructuring teams to include AI champions or experts who can guide others.

2) Trust, Privacy, and the Absence of a Direct CX Effect

Trust & Data Privacy was shown to be another crucial ingredient, strongly influencing operational transformation (H2 supported). This finding reinforces numerous studies emphasizing trust as key to technology acceptance in finance (Mohammad Ebrahimzadeh Sepasgozar et al., 2020; Byambaa et al., 2025; Lazo et al., 2023). When a bank's stakeholders trust its AI, initiatives can move forward faster and deeper. For instance, if customers trust a bank's use of AI for credit decisions, the bank can shift more of its lending process to AI, confident that customers won't revolt or regulators won't object. Similarly, if employees trust the output of an AI fraud detection system, they will rely on it more and integrate it into their daily workflow, thereby changing the operation. Our data thus validate the oft stated but rarely quantified notion that *"trust is an enabler of AI adoption."* We provide empirical evidence that trust/privacy is not just a nice-to-have sentiment; it materially contributes to how far AI is embedded in processes (β = 0.54, almost on par with workforce readiness).

However, the non-significant direct path from trust/privacy to customer experience (H4) is intriguing and merits discussion. It might initially seem counter-intuitive, since one would assume that if customers don't trust a system, their experience would be poor. The explanation lies in the fact that trust's impact happens upstream. In our model, by the time we look at Customer Experience, the trust factor has already done its work by influencing how much AI transformation takes place, and *that* transformation is what the customer experiences. In statistical terms, the effect of trust on CX is fully mediated by operational transformation. This finding is consistent with the idea that trust issues manifest as barriers to using AI (which H2 captures), but if those barriers are overcome and AI is implemented, customers judge the outcome by its quality, speed, etc., not by an independent trust factor. For example, if a bank has overcome trust concerns and successfully rolled out an AI-powered chatbot, the customer's experience with that chatbot will depend on its effectiveness (which comes from the underlying operational tech) rather than the abstract notion of trust because presumably if the customer is using it, a basic level of trust is already in place.

This result may also indicate that in contexts where trust is not violated (i.e., nothing has occurred to break trust), variations in trust levels don't create corresponding variations in reported customer experience. Customers usually notice trust only when it's lacking (a hygiene factor). In Cyprus, banks operate under strong EU regulations (GDPR, etc.), so there might be an assumption of privacy/security that customers take for granted. As long as those expectations are met, additional improvements in privacy or messaging around trust might not tangibly boost satisfaction – but failing to meet them would surely hurt. This interpretation aligns with the notion from Herzberg's two-factor theory: trust/privacy could be more of a "dissatisfier" if absent, rather than a "satisfier" when present in abundance.

For practitioners, the implication is nuanced: ensuring data privacy and building trust are necessary conditions for AI success, but by themselves they won't win customer delight – you still need to deliver functional benefits through AI. Banks must continue to safeguard privacy and communicate such efforts to maintain trust but should recognize that trust is a facilitator. They shouldn't expect customers to report improved experience simply because the bank is secure/trustworthy (customers already expect that); instead, trust enables the bank to deploy AI solutions that directly enhance experience. In summary, *trust is critical but works behind the scenes*. Losing trust would have a direct negative impact (and likely derail any AI-driven CX gains), but incrementally increasing an already sufficient trust level may not yield proportional CX gains unless accompanied by new AI-driven services.

3) Operational Transformation as the Mediator of Value

Operational Transformation emerged as the linchpin between the enablers (WR, TDP) and the outcome (CX). The large coefficient for OT → CX (0.67***) highlights that *what* *you do with AI internally strongly determines what your customers perceive*. This aligns perfectly with the service operations literature which holds that internal process quality drives external service quality (Heskett et al.'s Service Profit Chain, for instance). In our context, the findings imply that banks which meaningfully change their processes using AI – such as automating routine transactions, employing analytics to personalize offers, and improving decision speed – are seeing correspondingly high customer satisfaction and engagement gains. On the other hand, banks that only dabble with AI or implement it superficially (without operational change) likely don't see much difference in customer experience.

This mediating role of OT also helps explain some industry observations. Many banks pilot AI projects but often complain of "little ROI" or "no significant impact on customer satisfaction" from AI. Our model would suggest that in such cases, perhaps the AI wasn't scaled enough to truly transform operations, and thus customers felt no difference. The path from enablers to CX *must* go through actual operational changes. AI doesn't magically create value by its mere presence it's valuable when it fundamentally alters how service is delivered. This underscores a potential pitfall: organizations might invest in AI systems but under-utilize them due to organizational inertia, thereby failing to translate potential into reality. The strong mediation via OT in our results is a reminder that implementation is everything**.**

From a theoretical perspective, this finding contributes to the literature on IT business value and socio-technical change. It provides empirical support for the view that the benefits of advanced technologies like AI are *indirect* – emerging through process innovations and complementary changes (Melville et al., 2004; Melville et al., 2007). Our study specifically demonstrates this in the AI context and quantifies the effect in a service industry scenario.

For bank management in Cyprus and similar markets, the clear message is: focus on process redesign and integration when adopting AI. It's not enough to procure an AI software or launch a fancy AI-based app; banks should re-engineer their workflows to leverage AI's capabilities fully. This could mean reorganizing teams around AI tools, eliminating redundant human checks that an AI can perform, or creating entirely new service processes (e.g., predictive advisory services). The large R^2 for Operational Transformation (0.77) indicates that if a bank wants to benchmark itself, measuring its progress in AI-driven transformation is feasible and largely explained by how ready its people are and how much trust the environment has. Meanwhile, the high R^2 for Customer Experience (0.74) suggests our identified factors collectively are major determinants of AI-related customer satisfaction – thus banks aiming to improve customer experience via AI should concurrently nurture their talent (WR) and trust (TDP) to drive those internal changes.

4) Contextualizing Cyprus and Generalizability

Our research focused on Cyprus, a context that prior to this study had little empirical examination regarding AI in banking. Cyprus is a developed economy but with a relatively small banking sector, which is why understanding AI adoption here is valuable but it might differ from large markets. The results, interestingly, align well with global studies in terms of the pattern of relationships, suggesting that the fundamental mechanisms of AI integration are not so different in Cyprus. The workforce and trust factors were as important as elsewhere, and AI's benefits followed the same internal-to-external chain. This indicates a degree of generalizability: other mid-sized markets or late adopters can likely learn from these insights.

That said, a few contextual points are worth discussing. Cyprus, as part of the EU, has strict data protection regulations and a fairly conservative banking culture (due in part to recovering from past financial crises). Trust & Data Privacy scored moderately high on average in our sample (mean ~4.1/5), with relatively low variance possibly reflecting the regulatory baseline and common banking practices. Workforce Readiness had more variability across banks (some banks have invested heavily in digital skills, others less so). Operational Transformation and AI-driven CX were, on average, in the mid-range (~3.3–3.5/5), indicating that while some AI initiatives are underway, there's significant room for further transformation and customer impact. This overall picture fits the notion that Cyprus's banking sector is in an early-to-intermediate stage of AI adoption (Aristidou & Marcou, 2025). The positive relationships we found suggest that even at this stage, those banks that have pushed further on AI (with strong readiness and trust foundations) are already seeing noticeably better outcomes. It bodes well for the future as Cypriot banks continue to improve in these areas, we would expect customer experience to improve commensurately.

One could argue that in contexts with extremely low trust (e.g. markets with frequent data scandals) or extremely low skill bases, the model might behave differently. For instance, if trust was below a critical threshold, it might act as a bottleneck that prevents any transformation from happening at all, effectively making it a necessary condition. In our sample, trust levels were moderate to high, so we didn't observe a situation of trust deficiency halting AI projects entirely. Future research could explore such boundary conditions (see Limitations). Nonetheless, within the scope of our data, the interplay held strongly as hypothesized.

VII. Theoretical & Practical Implications

1) Theoretical Implications

Our study contributes to the academic discourse in several ways. First, it empirically validates that **technology adoption models need to incorporate organizational and contextual factors** to fully explain outcomes. Traditional technology acceptance models (TAM, UTAUT, etc.) are often user-centric and focus on perceptions like usefulness and ease-of-use for predicting individual adoption. We took a broader organizational lens (akin to HOT-fit or TOE frameworks) and showed that factors like workforce readiness (a human capital factor) and trust/privacy (an environmental factor) are pivotal in a complex adoption like AI in banking. The success of AI cannot be gauged by user attitudes alone; it requires examining whether the organization is ready and whether trust is in place. This supports and extends frameworks of organizational readiness for change (e.g., Weiner, 2020) into the specific domain of AI and customer-facing innovation.

Second, we integrate and test a full chain from **inputs to process to outputs** in the context of AI. Often studies examine either the impact of some factor on adoption *or* the impact of adoption on outcomes. We combined both, showing a mediated chain: readiness/trust → adoption extent (transformation) → performance (customer experience). This holistic approach aligns with calls in IS research to connect IT adoption to business value. Our findings echo those in the broader IT value literature that emphasize complementary changes (e.g., Brynjolfsson & Hitt's (2003) work) specifically, we provide evidence that human and cultural complements (skills, trust) drive process changes (AI usage) which drive service performance (customer satisfaction). We thereby contribute a concrete model for AI-integration success, which can be tested in other contexts or refined further (for example, adding additional predictors or outcomes such as financial performance, employee satisfaction, etc.).

Third, our study sheds light on the **trust-technology nexus**. While trust has been studied extensively in e-banking and online services adoption (e.g., the role of trust in mobile banking by Zhou, 2011), our model positions trust not just as a direct antecedent of usage, but as an organizational enabler that works through usage to impact value. This might influence how researchers conceptualize trust in future models: rather than always a direct predictor of intention or satisfaction, trust may sometimes be a facilitating condition whose effects are indirect. It prompts a more nuanced view: trust could moderate or mediate relationships rather than always have a direct main effect. In our case, one could say high trust was almost a precondition for high adoption, which in turn delivered satisfaction.

Finally, the research provides a benchmark for the level of AI-driven operational change needed to see strong customer outcomes. The high correlation between OT and CX (0.84) raises the question of whether at some point these constructs might even be part of a higher-order "AI success" factor. We chose to separate them to keep the causal logic (operations cause experience) clear. But the tight link suggests that maybe by the time you fully transform operations, customer experience is automatically elevated implying diminishing returns could set in (once operations are fully AI-optimized, further improvements in operations yield marginal CX gains). It might be interesting for future theory to consider at what point additional internal improvements don't translate to additional CX benefits (a nonlinear effect perhaps). While our data didn't show non-linearity in that relation, the high correlation hints that OT and CX almost move in lockstep at this stage of industry evolution.

2) Practical Implications

For bank executives and technology managers, our study offers a clear roadmap of priorities for AI integration:

1. **Invest in People:** The paramount importance of workforce readiness means banks must invest in comprehensive training programs on AI and data analytics for their staff. Beyond formal training, banks should create roles and structures that empower tech-savvy employees – for example, forming cross-functional innovation teams that include IT and business unit members to pilot AI projects. Hiring new talent with AI skills is another lever, but upskilling existing employees may be more crucial for broad readiness. Leadership should also communicate a vision that AI is an opportunity for employees (to augment their capabilities) rather than a threat, to build a culture open to change.

2. **Build a Trustworthy AI Framework:** Banks should continue to strengthen their data privacy and security frameworks to maintain stakeholder trust. This includes technical measures (robust cybersecurity, compliance with standards) and transparency measures (explaining how AI algorithms make decisions, perhaps using AI model documentation as suggested by Königstorfer & Thalmann, 2021). While our results show trust alone doesn't uplift CX, without trust the whole initiative can collapse. Therefore, managers should proactively address customer and employee concerns about AI – for instance, clarifying that AI recommendations are reviewed by humans or that customer data used in AI is anonymized and protected. Regulators and bank associations in Cyprus could help by issuing guidelines for ethical AI use, which in turn would shore up public trust.

3. **Focus on Process Change and Integration:** It's not enough to deploy isolated AI tools. Banks should aim for end-to-end process integration of AI. This might involve reengineering processes like loan approval, fraud monitoring, customer onboarding, etc., to incorporate AI decision-making at critical points. The goal should be to remove redundancies and capitalize on AI's strengths (speed, pattern recognition) while still providing human oversight where needed. The significant impact of OT on CX means banks will see customer satisfaction gains when, for example, loan approvals go from days to minutes, or when a chatbot resolves 90% of queries instantly. To get there, internal processes must be revamped – potentially requiring changes in policies, IT systems integration, and staff roles. Banks should consider iterative implementation: start with a pilot process, refine it, then scale up AI-driven processes across departments.

4. **Measure and Monitor AI Impact:** Banks should develop KPIs to track their progress in AI-driven transformation and its effect on customers. Our constructs provide some guidance: internally, metrics could include the percentage of processes automated by AI, number of AI-driven projects implemented, employee AI proficiency levels, etc. Externally, metrics like customer satisfaction scores for AI channels vs. traditional channels, net promoter score changes after AI implementation, or adoption rates of AI-based services by customers can be tracked. Monitoring these will help ensure that AI projects remain focused on delivering tangible improvements. If, for instance, a bank rolls out an AI chatbot but sees low usage or no uptick in

customer satisfaction, that's a sign either trust is lacking or the solution isn't meeting customers' needs – prompting a revisit of either the technology or the trust communication around it.

5. **Holistic Change Management:** The interplay of factors we found indicates that AI integration should be approached holistically. A bank that simply buys an AI system (tech focus only) without preparing people or addressing trust may fail. Conversely, a bank that trains people but doesn't actually push new processes won't see benefits. So, the recommendation is a synchronized change program: develop human capability, ensure governance and trust, *and* deploy AI in core processes simultaneously. Change management practices like involving employees in AI project development (to build buy-in and trust), clearly articulating the purpose and benefit of AI changes, and iteratively scaling successes can facilitate this holistic integration.

For the Cyprus banking sector at large, our findings are encouraging – they suggest that the levers for success are largely under banks' control (training, culture, internal processes) rather than external constraints. While smaller markets may not have the R&D budgets of big global banks, focusing on the organizational readiness and trust aspects can allow them to piggyback on existing AI solutions and still reap benefits. In practice, Cypriot banks could collaborate on certain AI training initiatives or share best practices in data governance to lift the whole industry's readiness and trust standards. Regulators might also find these results useful; knowing that operational use of AI improves customer service, regulators could encourage AI experimentation through sandboxes, while simultaneously insisting on proper risk management (to keep trust high).

VIII. LIMITATIONS & FUTURE RESEARCH

While our study yields valuable insights, it is not without limitations. First, the research design is **cross-sectional**, capturing a snapshot in time. This limits our ability to make strong causal assertions or to observe how the integration process unfolds dynamically. It's possible, for example, that as AI projects mature, the relative importance of factors could change (e.g., once AI is ubiquitous, trust might become an even bigger differentiator in usage). Future research could employ longitudinal designs, tracking banks over time as they implement AI, to see how improvements in readiness or trust lead to subsequent changes in operations and outcomes. Such studies could validate the causal direction assumed in our model and capture feedback loops (e.g., improved customer experience might further reinforce trust or prompt more investment in AI, creating a virtuous cycle).

Second, our data is based on **perceptions of banking professionals**, which, while informed, are still subjective. We did not include the voice of customers directly in this study. The AI-Driven Customer Experience construct is reported by employees/managers, essentially their perception of improvement in customer satisfaction. This was a necessary compromise, since linking directly to customer survey data was beyond our scope. Nonetheless, there is a risk of **single-respondent bias** employees might overestimate improvements or align their answers (e.g., those who said the workforce is very ready might also tend to say CX is high, simply out of optimism or consistency). We attempted to mitigate this by assuring anonymity and using different question sections, but it remains a consideration. Future studies could strengthen this by collecting **multisource data**: for example, using employee surveys for readiness/trust, but actual customer satisfaction metrics for CX, and maybe internal performance metrics for operations. That triangulation would add robustness and reduce common method bias. Additionally, qualitative follow-ups (interviews with bank managers or focus groups) could enrich the understanding, explaining the *why* behind some relationships, especially the non-significant ones like TDP→CX direct.

Another limitation is the generalizability beyond the context of **retail banking in Cyprus**. While we argued many insights likely carry over, each market has unique attributes. Future research can test our model in other countries, including both similar small-market contexts and larger economies. It would be particularly interesting to apply the model in developing countries where trust in technology or institutions might be lower, or in countries where AI adoption is at a much more advanced stage (like the US or China) to see if the same relationships hold or if new factors emerge (e.g., regulatory pushback could be a factor in more AI-saturated contexts). Moreover, while we focused on retail banking, the model could be adapted to other financial services domains (insurance, wealth management) or even other industries (e.g., healthcare, where AI is growing and trust/privacy are paramount). By testing the framework in different settings, scholars can assess its robustness and perhaps identify any industry-specific modifications needed.

Additionally, our study focused on four constructs, but there could be other relevant variables not included. For instance, **financial resources** or **IT infrastructure maturity** might also influence AI integration (though arguably these correlates with readiness and transformation). Also, **leadership support** or **strategic alignment** (part of Jöhnk et al.'s readiness categories) might be worth incorporating. We implicitly covered some of those under workforce readiness and trust environment (assuming supportive leadership fosters those), but future models might explicitly include top management support or AI strategy clarity as constructs. Similarly, **customer readiness** (customers' openness to AI) could be an interesting factor on the demand side that we did not measure. It might moderate the effect of operational changes on customer experience e.g., if customers are not ready or willing to use AI channels, then even well-implemented AI might not translate into a better experience because they won't use those services. Investigating such moderate effects would be a valuable extension.

Finally, the **measurements of constructs** could be refined. For example, our Trust & Data Privacy scale combined a few related aspects (security, privacy, trust in AI). Future research might separate these to see if, say, internal trust vs. customer trust vs. data privacy are distinct sub-dimensions with different impacts. The high correlation between OT and CX also raises a measurement question –

possibly some CX items (like speed of service) overlapped conceptually with OT improvements. Ensuring clear distinction in measurement (or modeling a second-order factor) could address that. We chose our measurement approach for parsimony, but alternative operationalizations (including using objective performance indicators for OT or actual customer survey results for CX) would strengthen validation of the model.

Despite these limitations, we believe the study provides a useful foundation and framework for understanding AI integration in banking. It highlights key levers that researchers and practitioners should pay attention to. The next wave of research can build on this by exploring the nuances and boundaries as described. For instance, a compelling future study could be a **comparative case study** of two banks (one that succeeded in AI integration and one that struggled), analyzing their differences in workforce training, trust-building, transformation approach, etc., to qualitatively complement our quantitative findings.

IX. CONCLUSION

Artificial intelligence stands at the forefront of innovation in retail banking, but harnessing its potential requires more than just technology deployment – it demands readiness among people, trust in systems, and a willingness to transform organizational processes. Our study in the context of Cyprus's retail banking sector reinforces this reality. We found that banks derive significant improvements in customer experience from AI **only when** they have invested in building an AI-ready workforce and fostering a trustworthy, privacy-conscious environment that allows AI to be woven into their operations. In our SEM analysis, these factors explained a large share of the variation in how deeply AI was adopted into operations (77% of variance) and how much customer experience improved (74% of variance). Workforce readiness and trust/privacy emerge as powerful enablers, while the extent of operational transformation is the key conduit through which AI creates value for customers.

In practical terms, a bank's journey to AI-fueled success should begin with its people and culture, ensuring employees are equipped and enthusiastic to collaborate with AI. Simultaneously, maintaining stakeholder trust through robust data ethics and transparency is non-negotiable. With these foundations, banks can then drive meaningful process innovations from automating routine tasks to delivering personalized services that customers tangibly appreciate in the form of faster, smarter, and more convenient banking experiences. Banks that neglect the human and trust elements may find their AI initiatives stalled or yielding lukewarm benefits.

For the Cypriot banking sector and similar markets, the implications are clear: focusing on human capital and trust can accelerate catching up with global leaders in AI implementation. Even smaller banks can compete on customer experience if they smartly implement AI where it counts and ensure customers feel confident and comfortable with those innovations. From a scholarly perspective, our research contributes evidence that successful technology integration in service industries is a socio-technical endeavor, marrying high-tech with "high-touch" management of human and cultural dynamics.

In conclusion, the integration of AI in retail banking is not a mere IT project, but a transformational journey. Those banks that treat it as such aligning strategy, preparing their workforce, cultivating trust, and reinventing processes are likely to unlock the full promise of AI. And that promise is compelling: a banking experience that is more efficient, personalized, and responsive to customer needs than ever before. As AI continues to evolve (with emerging trends like generative AI on the horizon), the principles evidenced in this study will remain relevant. Organizations that balance technological prowess with human readiness and trust will be best positioned to turn AI's potential into realized performance and satisfaction. The future of banking belongs to those who can seamlessly integrate the algorithm with the human touch, and our study provides a stepping stone in understanding how to achieve that integration.

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The preferred spelling of the word "acknowledgment" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgments. Avoid expressions such as "One of us (S.B.A.) would like to thank ... ." Instead, write "F. A. Author thanks ... ." **Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page**.

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