



Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David



Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David

PREPARED BY: KOMAL IRSHAD

STUDENT NUMBER: 2521536

PRESENTED TO: PROFESSOR EBAD BANISSI

COURSE TITLE: RESEARCH PRINCIPLES AND PHILOSOPHY (LCDB7007)

Table of Contents

Assessment Title:	4
Abstract:	4
CHAPTER 1	5
Introduction	5
Background	5
Research Context	6
Research Problem / Gap	7
Purpose of the Research	8
The aims of this study are to:	9
Key Definitions	9
AI-Driven Personalisation:	9
Financial Inclusion:	9
Consumer lending:	9
Emerging markets:	10
Responsible AI:	10
Absorptive capacity:	10
CHAPTER 2	11
Method for Conducting the Literature Review	11
Search strategy	11
Search terms	11
Inclusion criteria	11
Exclusion criteria	11
Screening process	11
Analytical procedure	12
Limitations	12
CHAPTER 3	14
Critical Literature Review	14
Theme 1: Financial Inclusion in Emerging Markets	14
Theme 2: Personalisation using AI in financial services	15

Theme 3: Strategic Management and Digital Transformation.....	16
Theme 4 Research Philosophy in AI and Financial Services Research.....	18
Theme 5: Ethical AI, Governance and Responsible Innovation	19
Theme 6: Literature synthesis and gaps in the research.....	21
CHAPTER 4	24
Philosophical and Methodological Analysis	24
Study Overview	24
Ontological Analysis	25
Epistemological Analysis	25
Axiology and Researcher Positionality	25
Methodological Quality	26
Ethical Considerations	27
Critical Appraisal.....	28
CHAPTER 5	29
Discussion and Contribution	29
Theoretical contribution:	29
CHAPTER 6	32
Conclusion	32
References	34

Assessment Title:

The Role of AI-Driven Personalisation in Financial Inclusion: A Strategic Framework for SME and Consumer Lending in Emerging Markets

Abstract:

Artificial Intelligence (AI) is on the rise to become a tool that can help fill the financing gap for Small and Medium Sized Enterprises (SMEs) and consumers in emerging markets. But the body of research supporting the statement is disjointed, and the underlying philosophies such as assumptions are not always subjected to analysis.

This research examines the recent literature on personalisation in financial services using an AI tool and considers AI a strategic management tool rather than just a technical object, with a view to the discussion being set in the context of research philosophy and traditions and strategic management.

A systematic literature search in the business, management and information-systems literature and analysis of the identified literature thematically synthesizes literature on financial inclusion, AI-based personalisation, strategic management theory, research philosophy and responsible-AI governance. One of the recent empirical studies is then treated in detail in a philosophical and methodological manner and the ontological and epistemological commitments of the study and their implications for what the study can and cannot claim are addressed.

There is a prevailing positivist and accuracy-of-prediction approach in the current literature and little consideration is given to organisational competence, managerial decision-making and the philosophical underpinnings of both. The review also clarifies the difference between the capability of organisations and the real gains in financial inclusion, which is often overlooked in the literature.

The resulting research gap is the foundation for his proposed doctoral study and finds that a pragmatic, mixed-methods approach is appropriate for studying personalisation as a strategic and organisational phenomenon in emerging-market lending with the support of AI. Instead of asserting theoretical progress at this point, the review highlights the specific opportunities for theoretical integration between the strategic-capability and values of inclusion and responsible-AI perspectives, that the proposed doctoral research would then take up the empirical approach.

CHAPTER 1

Introduction

Background

Financial inclusion, defined broadly as making available and equally accessible to individuals and enterprises formal financial services, has been one of the key policy and corporate issues for the last decade (World Bank, 2025). Given these aspects, artificial intelligence (AI) has transitioned from being a secondary back-office solution to an integral part of banks, microfinance organizations, and fintech companies to serve underserved or unbanked populations. AI-based personalisation uses machine learning, predictive analysis, and other information sources to customize credit evaluation, product development, and customer interactions for particular people or businesses, instead of imposing a standard, one-size-fits-all strategy. (Kshetri, 2021) In emerging markets, the lack of credit history and limited collateral has historically deterred large portions of the population from accessing formal credit and “revolutionary” usage patterns for mobile applications can instead be used to obtain documentary evidence, as can utility payments and transaction history.

This assumed optimism is balanced, however, by a countervailing risk that the research in this paper posits as its central tension from the beginning: at the same time AI is expanding access to loans, it is also creating new and less obvious ways to exclude, opacify, and discriminate. The expansion of who can be counted does not equal the expansion of who is truly and meaningfully included, and that is where much of the critical analysis in this research occurs.

There is a significant rate of change. Reports indicate that AI is influencing lending decisions by automating the process of approving loans, broadening the range of information considered to assess client creditworthiness and altering how clients interact with lenders with the use of chatbots, robo-advice and offers dynamically tailored to every client. Moreover, it's subtly reshaping what it means to be "accessible. Further, it's reshaping the meaning of “accessible” finance by focusing on algorithmic reach. This mix of technological know-how and developmental urgency is why AI-powered fintech has become a hot topic for practitioners and policymakers, despite the academic literature's inability to keep pace with the pace of commercialization.

It is important to give special attention to the mechanisms by which this is done, as much of that which follows depends on these mechanisms. The classic underwriting process is based on a set of verifiable requirements, such as income, credit bureau score, valuation of collateral, etc., that is performed by a loan officer working with an institution's underwriting ruleset. Instead, a much richer and more continuous stream of signals is fed into a personalisation system powered by a machine learning algorithm, which adjusts its quantification based on new data as it comes in, and which many implementations return a

decision—but also a customised product offer (such as interest rate, repayment schedule, credit limit) specific to that individual applicant. This change does not only affect who gets approved, but who approves, on what basis, and why the decision is contestable when something goes wrong – questions that lie more in the realm of strategic management and governance literature than in computer science, as this research does. This question of contestability — expanding access on the one hand, contracting accountability on the other — is one that continually comes up in the rest of this research.

Research Context

In this research the empirical setting has been differentiated from its literature context. The term "emerging markets" is employed throughout to denote the context in which the literature reviewed has been conducted: The literature reviewed for this article comes from the vast majority of emerging-market contexts (South and Southeast Asian, African and Latin American settings). On the contrary, Pakistan is the empirical context of the doctoral research that this review advocates. The two are different but not contradictory, but the rest of this section explains why Pakistan is useful as that setting, not only because of personal and logistical factors but also because of theoretical ones.

This study is set against the background of the continued gap between the aspirations of digital financial inclusion and its uneven fulfillment. Global account ownership has increased to 79% from 74% in 2021, according to the World Bank's Global Findex Database 2025, mostly due to the uptake of digital payments and mobile phone usage (World Bank, 2025). The same data, however, show that there is a significant underrepresentation of women and lower-income groups, with a large proportion of adults who are not included saying that it was because they did not feel confident in the financial system, not necessarily because they were not reached (World Bank, 2025). The financing gap is even wider at the enterprise level: the World Bank Group (2025) estimates that USD 5.7 trillion of funding is needed for small and medium enterprises (SMEs) in 119 emerging market and developing economies (EMDEs). This disparity is particularly impacting on women-owned businesses (International Finance Corporation (IFC), 2025).

This is more realistically demonstrated in Pakistan. SBP and other allied fintech agencies have, for more than a decade, encouraged digital account usage and branchless banking; however, formal account ownership and SME credit penetration are still lagging behind those of other South Asian markets, and there are gender gaps in account ownership, even as mobile-phone penetration has grown rapidly. If that is the case, then the practitioner familiarity is just the one thing that makes Pakistan useful, beyond the theory, because the combination of a coercive, regulator-led approach to inclusion targets (see Theme 1 below) with an active fintech and microfinance sector with established experience in personalisation through AI and an institutional credit gap large enough that the strategic-capability question this research asks — does capability building actually lead to inclusion, or only to

performance? — isn't just an academic distinction, but has real stakes. This is an unusual mix of regulatory pressure, adoption maturity and outcome uncertainty, and is not convenience that makes Pakistan worth using as an empirical basis for the proposed doctoral research, but the mix of these three factors.

AI-powered digital transformation is among the policies that can address this gap, in addition to the more traditional ones such as credit guaranty programs and regulatory reform. But “responsible AI” is also an agenda that has emerged beside it, and sometimes in opposition to it. International bodies such as the World Bank, the IMF and the OECD are increasingly interpreting “financial inclusion” as access to financial services without the imposition of new forms of discrimination, over-indebtedness or opacity.

Research Problem / Gap

Despite the swift introduction of AI across emerging nation banks, micro-finance organisations and fintech firms, the research foundation has not been developed in a balanced manner. Most of what has come out so far relates to the question of whether the machine-learning model predict default better than the traditional scorecard did. This has led to a vast and continually expanding body of technically competent work, but it often suggests that the financial institution is a passive adopter of a tool, the organisation has to create capability around that tool, learn to take new types of risk, and make conscious strategic choices on how far to go with it in making lending decisions.

The narrow framing has implications beyond the research literature itself. In banks and fintechs, procurement and vendor-selection decisions are made primarily based on the accuracy of the model in the pilot project, and downstream inclusion impact, organisation readiness, staff retraining and escalation procedures for cases of disagreement, are considered as secondary implementation issues – or are left to later. The research gap found here is not only academic, but it also reflects a gap in evaluation and adoption practices in financial institutions.

This is not just one single gap, but it's better to break this gap down into four parts, and that's more manageable for an input from the DBA.

Empirical gap. There is comparatively little empirical evidence in Pakistan that speaks to whether AI-powered personalisation translates into measurable, borrower-level inclusion gains, compared to institution-level gains in performance (to be developed further in Theme 6).

Theoretical gap. To date, there are no models that link together capability-building in the organisation and inclusion outcomes and ethical governance in one account, as developed in Theme 3 and Section 5, with the Dynamic Capabilities model, the Resource Based View, and the Technology Acceptance Model.

Methodological gap. The dominant quantitative, cross-sectional, theory testing designs employed in this literature (as critiqued in Section 4 by Abdurrahman et al., 2024) are incapable of demonstrating that capability building would lead to inclusion over time, suggesting a need for mixed-methods enquiry.

Philosophical gap. The positivist underpinning of researchers' work, and their commonly unexamined ideas about what constitutes evidence of inclusion, bias the findings of a study beforehand, as discussed in Theme 4 and Section 4.3.

Among the four, the philosophical gap is addressed as the first one, logically, since it is the gap that is addressed by the researcher's decisions in the other three: what constitutes adequate empirical evidence (i.e, the empirical gap) depends on how a researcher resolves questions of ontology and epistemology; what is treated as a theoretically viable versus contested theoretical construct will depend on the same decisions, as will the defensible methodology for the research question (i.e, the methodological gap). The empirical, theoretical and methodological gaps are therefore considered as a consequence of and a reason for the philosophical gap.

What's missing is sometimes more difficult to measure and that might be why it's been ignored. The literature on personalisation through AI is largely limited to the use of AI as a software tool, with very little research focusing on the potential of AI as a strategic organisational capability. Moreover, there is limited knowledge of the governance of "responsible AI" from theory to practice in the context of lending. Furthermore, it is not known how the human manager will understand, override and defer to an algorithm's output when actually deciding on lending.

An important question that needs to be addressed in relation to these research issue is what is the philosophy behind using tools to study these issues. These assumptions are connected to the notion of what financial exclusion is, and what kind of knowledge is considered reliable in terms of the AI system's functioning, as well as the researchers' stance and beliefs. These assumptions are typically not stated, but they have a major impact on what a study might find. If it doesn't challenge its own assumptions, a study will not be able to tell if AI personalisation is actually closing the inclusion divide or if it is simply obscuring inequities in an algorithm.

Purpose of the Research

The research aims to address a single research question: What are the current philosophical and methodological conceptions of AI-driven personalisation and financial inclusion in emerging-market lending and what are their implications for knowledge? The following four aims do not constitute stand-alone activities, but rather represent a way to elucidate the question above.

The aims of this study are to:

- (i) review critically recent literature on personalisation, financial inclusion and strategic management of digital transformation in banking, focusing on identifying the philosophical assumptions that each strand of literature makes and what they enable it to assert;
- (iii) analyze the philosophical underpinnings that underlie this literature, namely positivist, interpretivist, critical realist and pragmatist; and
- (iii) discuss the methodology of the studies that have been reviewed and tie the discussion clearly to the philosophical assumptions discovered in (ii); and
- (iv) critically analyse one empirical study in detail, examining the ontological, epistemological and axiological bases of the study and how these bases relate to the methodological decision that was made for the proposed doctoral research.

Key Definitions

Some of the terms employed in this research have not reached an agreed definition and the following definitions are kept intentionally short with a note on the point of contestation provided at the end of each definition.

AI-Driven Personalisation:

Using machine learning, predictive analytics, and non-traditional data to make a credit decision, product, or customer interaction as unique to each individual borrower or firm as possible, instead of sticking to a single set of fixed criteria (Kshetri, 2021). The definition is not what is in contention, it is just that those decision rules update based on the data, and not driven by a human rule-writer. This research does not make a semantic distinction between the two; it is a substantive one.

Financial Inclusion:

How inclusive are financial products and services to individuals and businesses in terms of their availability and use, whether meaningful or not; World Bank Global Findex framework. The contested element is the access/use distinction itself: statistics about account ownership can be used as proxies for inclusion, but as several of the sources reviewed below show, these proxies are becoming less reliable: accounts opened but not used count as access but not inclusion.

Consumer lending:

Credit granted to an individual for personal, non-business use, such as a personal loan, buy now, pay now, or buy now, pay later agreement, credit card, or a small emergency loan.

SME lending is a type of credit that is provided to small and medium size businesses (SMEs), which are characterized by an information gap between the borrower and the lender (World Bank Group, 2025).

Emerging markets:

Economies that are rapidly transforming structurally and financially, have lower formal account ownership, a significantly larger informal sector and financial infrastructure that is still being built up compared to high income economies. The term refers here to the geographical range of the literature; Pakistan is not a synonym of the literature, but is its specific empirical referent.

Responsible AI:

The governance arrangements that are planned to ensure fairness and transparency in AI-based financial decisions, avoiding discrimination against specific groups (European Parliament and Council of the European Union, 2024). It can only exist as a concept because AI systems can be fair on average, but unfair to a particular group: For instance, if a bank uses alternative data to score borrowers who have no scores, this might inadvertently contain information about gender, location, ethnicity, etc. without these characteristics being used directly. What is questioned and what is also revived in Theme 5 is whether the concept of "responsible" can be captured sufficiently with a procedural approach (consent, disclosures, testing) or whether it demands a substantive approach, one that is not necessarily based on the requirements of procedural compliance.

Absorptive capacity:

The capacity of an organisation to identify the value of new external knowledge or technology, to assimilate it, and to use it for commercial purposes (Cohen and Levinthal, 1990). In this research it describes how two banks in the same regulatory environment and using the same AI vendor can experience vastly different inclusion results, as the differences are primarily about the data infrastructure and the analytical skills (experience) that each bank has on board.

CHAPTER 2

Method for Conducting the Literature Review

Search strategy

The review is conducted using the Scopus, Web of Science, ScienceDirect, Emerald Insight, ABI/INFORM and IEEE Xplore as well as Google Scholar for grey literature, and institutional reports (especially World Bank and G20/IFC reports), which play an important role in the policy discussion on financial inclusion but are not indexed in academic databases.

Search terms

The search was conducted using terms for three clusters: technology terms (artificial intelligence, machine learning, AI personalisation, explainable AI, responsible AI, algorithmic credit scoring); inclusion terms (financial inclusion, SME lending, consumer lending, fintech, digital finance, emerging markets); and theory terms (dynamic capabilities, resource-based view, technology acceptance, institutional theory, research philosophy). To narrow down the results, boolean combinations ("artificial intelligence" AND "financial inclusion" AND "emerging markets") were used.

Inclusion criteria

The focus was on peer-reviewed journal articles published in English from the period 2020–2026 from business, management, finance, and information-systems journals and outlets, and the foundational theoretical works that were published prior to this period (e.g., Barney, 1991; Teece, Pisano, and Shuen, 1997) served as key theoretical reference in the contemporary literature.

Exclusion criteria

Technical papers on machine-learning systems that were purely algorithmic in nature, without managerial/ organisational aspects, and conference abstracts without full text, opinion papers with no empirical or theoretical contribution and studies not in the business/ management/ finance/information systems domain were omitted. A careful rather than prescriptive application of this boundary was adopted – where the results of a technical paper had direct relevance to algorithmic bias or explainability (Theme 5), it was not deleted simply because it was a "technical paper". For technical reasons only papers were not included when they only featured and discussed model architecture or computational performance and did not mention any managerial or governance implication.

Screening process

The screening was not done in one shot. The initial pool of records identified through database searches was subjected to screening of titles and abstracts to remove clearly irrelevant and purely technical results and then the full texts were read and assessed for relevance to the four theoretical clusters, prior to thematic synthesis, and the reference lists

of key papers (e.g., Vial, 2019; Fuster et al., 2022) were hand searched for additional relevant papers that might not have been identified in the initial searches. The numbers below are approximate and do not constitute a formal PRISMA count as this was considered as an assignment of literature review (not systematic review).

Database / source	Example search string	Date range	Initial results (approx.)	Retained after screening
Scopus	"AI" AND "financial inclusion" AND "emerging markets"	2020–2026	~140	18
Web of Science	"artificial intelligence" AND "credit scoring" AND "bias"	2020–2026	~95	11
ScienceDirect	"dynamic capabilities" AND "digital transformation" AND "banking"	2020–2026	~120	9
Emerald Insight	"responsible AI" AND "governance" AND "banking"	2020–2026	~60	6
ABI/INFORM	"fintech" AND "financial inclusion" AND "Pakistan"	2020–2026	~40	4
IEEE Xplore	"explainable AI" AND "credit"	2020–2026	~55	3
Google Scholar / grey literature	World Bank; G20/IFC; central-bank reports	2020–2026	~30	7

These are approximate figures of records screened and retained per source, to ensure that the screening process is transparent and can be audited, but are not comprehensive logs of an export from the database.

Analytical procedure

Sources were not grouped according to technology type or chronologically, but thematically to emphasise the conceptual and philosophical arguments included within the research framework. The competing theoretical lenses for each subject have been explored, and critically appraised in terms of their explanatory capacities, and cross-cutting areas of research gaps have been identified inductively across the themes.

Limitations

There are three limitations to be taken into account. First, the field of AI and fintech is evolving at a rapid pace, and a review may quickly become obsolete as new papers are published in the coming months; many of the papers referenced here have been published in 2025–2026, and it is likely that other significant additions have been made since the writing of this work.

Second, there is an issue of publication bias, as research showing positive outcomes related to AI-driven inclusion could be more widely published and promoted by technology vendors and financial institutions than research showing no effects or negative effects. Thirdly, the literature shows a geographical concentration in the case settings of South and Southeast Asia and Africa, with fewer studies coming from Pakistan, and a general absence of longitudinal studies that would be able to track whether the inclusion through AI is enduring after novelty and marketing impacts subside.

The 4th restriction is language and format. Limitations in scope to English-language, peer reviewed, journal-based publications may result in a lack of representation of relevant Urdu-language policy debate, central-bank circulars, and practitioner analyses produced in Pakistan, which may discuss AI-powered lending, but which this review does not otherwise prioritise. For the cases where such material was found in the grey-literature search, it was used with caution and cross-checked with at least one peer-reviewed or institutional source before being included but it is possible that locally significant developments were overlooked.

CHAPTER 3

Critical Literature Review

Theme 1: Financial Inclusion in Emerging Markets

The theme is built around a series of questions: who gets included, under what conditions and who might be left out even with AI-powered lending services? To answer it, financial inclusion needs to be understood as a means of proving, rather than a means to take for granted.

The literature has three conceptions of financial inclusion. In development economics, financial inclusion is considered as a means to poverty alleviation and enterprise development, and the fact of holding an account with a bank or being able to access formal credit is used as indicators of participation in the economy. The SME financing gap, which is USD 5.7 trillion, across 119 EMDEs, is more specifically covered by financial inclusion theory, which focuses on mechanisms of exclusion, such as collateral requirements, documentation demands, geographic branch distribution and product design, that keep individuals and firms out of the formal system. This gap is often cited as a measure of the size of the challenge (World Bank Group, 2025; IFC, 2025). By contrast, institutional theory addresses the question of why financial organisations behave in the way that they do: DiMaggio and Powell (1983) describe how, as well as being locally optimal, financial organisations can also be pressured into adopting broadly similar AI-driven inclusion initiatives by the pressure of coercion from regulators, the pressure of normativeness from professional and industry bodies, and mimetic pressure to emulate each other.

These three kinds of lenses are not mutually exclusive, but they point towards different units and levels of analysis. Development economics yields indicator-based research at macro level (such as Global Findex trend analysis), while institutional theory offers a drive to do research on the organisational level with questions of "why" and "how": why and how do individual banks take up personalisation via AI? But the current literature suffers from a major drawback: it is very rarely combined; studies reporting on inclusion gains from the inclusion of aggregates mention little about the institutional and organisational processes that produced them and vice versa, institutional and organisational studies of bank digitization rarely refer to population-level inclusion gains. This is exactly where financial inclusion as an outcome and digital financial access as an enabler meet: documenting access at the population level does not require that the newly reached financial consumers or producers are in actual meaningful and sustainable financial inclusion; and existing structural barriers, such as gender, informality, institutional trust, and financial literacy, can still stand beneath the aggregate level of financial access.

Finally, the financial inclusion agenda in emerging markets is often driven by regulatory and development-finance institutions and international organizations, rather than by banks' own strategy, as was often the case in both strands. This is relevant because, in his typology, DiMaggio and Powell (1983) describe a coercive-isomorphism mechanism which is more likely to prevail in situations like Pakistan, where the central bank and international donors explicitly establish inclusion goals, and banks are required to report on these goals. A comparison of the emerging-market situation with the case studies in the institutional-theory literature on digital banking, which are largely from North America and Europe, might suggest a more pronounced role for regulatory compulsion in the former, which could lead to a misrepresentation of the why in a purely voluntary, competitively-driven account of banks pursuing inclusion efforts through AI.

Theme 2: Personalisation using AI in financial services

Rather than a description of applications, this theme around bias, opacity and privacy, versus predictive accuracy, expanded access and personalisation is developed around the tension. The tension from which the studies reviewed below emerge is a tension that has to be made explicit rather than a collection of ever-growing evidence of the inclusion benefits of AI.

Technically on the access side, most of the work in this space is related to AI-driven credit scoring and/or personalisation, from a technical or a performance perspective. What is common to this literature is the use of alternative data to machine-learning models that create dynamic credit scores for populations lacking traditional credit files, such as mobile usage, utility payment records, digital-wallet transactions, and even psychometric data, on all of which African countries, as well as countries in South Asia and Latin America, are featured. Related, though not so comprehensive, is recent evidence from Pakistan that AI-powered digital lending platforms foster positive financial inclusion outcomes, which then have a positive impact on SME growth and green-entrepreneurship outcomes, while also highlighting regulatory, technological and digital-literacy challenges that hinder the effectiveness of these mechanisms (Raza, Wahab and Madad, 2026). The cautionary note: this finding is in a new journal that has a rather limited index, and the structural-equation-modelling design is not a different one from the one that was criticized in Theme 4 below, which has objectivist and positivist assumptions. Nevertheless, it is one of the few empirical studies on this question so far conducted in Pakistan and the dearth of scholarship on this issue itself provides indication of the state of the field, which this research revisits in Theme 6.

Here, the accuracy – fairness trade-off, which emerged in full in Theme 5, is directly relevant: Models that process other data can enhance access to the scoring system, yet they may also embed proxies for gender and location (or ethnicity) that create new, less overt forms of exclusion in that broadened pool. The personalisation/exclusion dichotomy is not a tension between different studies, it is a sign of the same underlying process, this is where the central

tension in this theme can be found in the broader literature: treating "AI expands access" as a fact, rather than a claim that needs to be substantiated with evidence.

According to the theory, the entire body of work is based on four frameworks which are built unequally. The TAM (Davis, 1989) has been applied to individual-level phenomena like consumer and small-business use of digital financial services, and explains adoption at the individual level of perceptions of usefulness and ease of use; however, the individual-level focus of TAM does not explain phenomena at the organisational level, for example, how a bank can develop AI governance capabilities. The Technology-Organisation-Environment (TOE) concept, which adds organisational and environmental (including regulatory) factors to technological factors, has been directly applied to Digital Transformation and Dynamic Capability Development in banking and has helped to address this gap. Building on the work of Barney (1991), the Resource Based View (RBV) sees AI and the data it draws from as valuable, rare, inimitable and non-substitutable resources that have the potential to create a competitive advantage, while Dynamic Capabilities theory describes how these resources are sensed, seized and reconfigured over time.

While both TAM and TOE, when examined critically, are valuable in explaining the adoption decision, they offer less insight into what can happen after adoption, such as the deployment of AI-enabled personalisation in a responsible way, the strategic capability to do so, or as merely a superficial digital overlay on a largely unchanged lending practice.

Theme 3: Strategic Management and Digital Transformation

Recent research on digital transformation in banking has been focused on the Dynamic Capabilities theory developed by Teece, Pisano and Shuen (1997) as a core element of how firms detect opportunities and threats, respond to them by reconfiguring their resources and capabilities, and then transform their internal capabilities to sustain competitive advantage during fast pace of technological advances. New applications have introduced the concept of Dynamic Capabilities and the RBV together to capture the innovation performance of digital products in banking, suggesting that the mere presence of digital and data resources is important but not enough: firms need to acquire the agility and adaptability to make good use of those resources, and digital transformation is often seen as a mediating factor between the possession of resources and innovation outcomes (Vial, 2019). Other recent work merges Dynamic Capabilities with the TOE framework to explore the development of necessary capabilities to support digital transformation and innovation in banks, including Abdurrahman et al.'s (2024) survey-based study of 48 banks in Indonesia. Systematic reviews of "digital dynamic capabilities" more generally describe an interconnected sensing-seizing-transforming process, in which banks react to technological disruption, and which has historically been speeded up by external shock events (such as the financial crisis of 2008).

The Knowledge Based View adds another layer to the RBV by identifying the potential advantage of the tacit and codified knowledge that is embedded within an AI-based personalisation system, not the system itself. Given that the algorithms can be licensed or

replicated by competitors, it is easier to replicate an organisation's accumulated data and interpretive expertise. It is important to note that Strategic Capability Theory generally supports the notion that the competitive advantage in AI-based lending will not be technological, but will instead be about the capability of an organisation to connect the technological potential to consistent strategic action.

There is another complementary lens that can be used in conjunction with absorptive capacity theory, and that is the lens of the "Wetland" wetland. Cohen and Levinthal (1990) state that the capacity for a firm to value, assimilate, and commercialise new external information is a skill that has to be developed over time through previous investments in related areas – such as data infrastructure, analytics expertise, and digital product development – and not simply acquired through a vendor contract. This impact is directly relevant to the emerging-market banking landscape: incumbent banks that have limited prior investments in digital technology might not be able to catch up on the pace of AI incorporation as fast as more digitally native challenger banks or fintech bankers, in part helping to explain why we see a variation in the speed of AI adoption and inclusion outcomes between banks operating in the same regulatory environment.

Since there are already several frameworks in the literature, it would be more useful at this point to be clear about what each explains and where each's explanatory range ends.

Theory	Level of analysis	What it explains	Limitation for this study
TAM	Individual	Technology adoption decisions	Weak organisational focus; says little about post-adoption governance
TOE	Organisation / environment	Conditions for adoption	Limited explanatory power once adoption has occurred
RBV	Firm	Strategic resources and competitive advantage	Limited ethical or inclusion dimension
Dynamic Capabilities	Firm	Capability development and change over time	Does not directly explain inclusion outcomes
Responsible AI (governance)	Governance / algorithm	Fairness and accountability	Limited strategic-capability explanation

The table indicates a division of labour, not a race between theories—where does a bank get its personalisation capability from? (TAM/TOE); how does the bank develop that capability? (RBV/ Dynamic Capabilities); is the personalisation system fair and accountable? (responsible-AI governance frameworks). None of the lenses covers all three questions, as was postulated in Section 1.3, and will be expanded in Section 5.

Strategically, literature on financial inclusion is rich in theory and poor in empirical evidence. While various dynamic-capabilities studies related to banking digital transformation focus on the firm-level outcomes like innovation or sustainability, few explicitly connect the dynamic capability building processes to the outcomes of inclusion for previously unbanked SMEs or consumers. This is a second research gap; the processes through which organisational competency maps onto inclusive outcomes are not as well understood.

Theme 4 Research Philosophy in AI and Financial Services Research

Labeling a study as "positivist" or "interpretivist" is a beginning, not an end; as described in the coursework brief, theory, epistemology, ontology and axiology, and what they imply about the nature of knowledge, should be critically reflected upon, and each of the philosophy below are explored in the context of answering those four questions: What does it assume reality is? What is the definition of knowledge? What methods follow? What emerges and what is left out, that is, — what becomes visible and what invisible — as a result of these studies?

The five research philosophies mentioned in the well-known "research onion" framework of Saunders, Lewis and Thornhill (2023) are relevant for the purposes of this article when it comes to research in the field of AI and financial services. The positivist approach has an objective, mind-independent organisation that is captured by hypothesis testing and measurement (dynamic capability, banking performance), favours quantitative, deductive designs and views efficacy of an AI lending model as an objectively measurable property. It is applied to the problem of predicting the accuracy of the algorithm, and makes this information visible, meaning that the lived experience of the borrower determining the algorithmic decision is largely invisible — this is typical of predictive accuracy in AI credit scoring systems, where the predictions are seen as an objective, quantifiable (and therefore measurable) result. Interpretivism, on the other hand, holds that social reality is negotiated by the actors through their construction of meaning, that knowledge is always local and will be situated in a specific context, and that it employs qualitative and inductive methods, as it is concerned with the subjective interpretation and actions of the actors in relation to the algorithmic outputs (Alharahsheh and Pius, 2020). It brings managerial and borrower sense making into view but restricts the evidence that is generalisable and comparable, as regulators and inclusion targets often require — which is barely present in the highly technical literature reviewed above.

Critical realism is a middle ground approach which recognizes the existence of an objective reality beyond human thinking (Bhaskar, 1975), such as the true decision logic behind an AI model, and also claims that interpretations of reality by human actors are always subjective and socially situated (Alharahsheh and Pius, 2020). It takes a mixed or layered approach, targeting to separate the underlying mechanisms from the interpretation, by revealing the technical mechanics of an algorithm and the organisational sense making around it, that this research's own research questions are aiming for. This position is appropriate for

a research question that has to be approached with both genuine regard for the organisational stories that are told around an algorithm and technical understanding of how the algorithm works.

By choosing ontological and epistemological convictions based on the particular research issue and generally endorsing mixed-methods designs, pragmatism denies the primacy of any one philosophical stance (Saunders, Lewis, and Thornhill, 2023). It takes the research question, rather than a prearranged philosophical stance, as the determining factor of method, unveiling whatever combination of quantitative and qualitative evidence a defensible position will reveal, as opposed to the one-paradigm design philosophy. In the context of AI research for financial inclusion, pragmatism is particularly relevant due to the dual nature of research problem that is identified in this research, which requires a defensible and somewhat measurable description of the outcomes of financial inclusion and a deep understanding of managerial decision making and governance practice.

The fifth philosophy, postmodernism, is even more radical as it views concepts like 'creditworthiness', 'financial inclusion' and even 'fairness' as discursive constructs that are created to serve a specific institutional interest, and doubts that one research design can yield neutral and generalisable knowledge about them (Saunders et al., 2023). It reveals the interests that a definition of "inclusion" or "fairness" is serving, at the expense of the actionable, comparable results practitioners and regulators are seeking. In this context, a postmodern view would question whose interests are being represented when they view financial exclusion as a problem of data availability that can be solved with enhanced algorithms, instead of, say, representing the interests of those who were not adequately compensated for paying for financial services, or the interests of branch networks in particular areas that were not adequately invested in historically. Very few of the studies included in Themes 2 and 3 consider this question, nor do they present arguments to defend philosophical assumptions in this literature; this is a recurring theme throughout this research.

These assumptions impact on the evaluation of AI, loan research, management decision making and organisational studies. Its importance is illustrated by the nature of creditworthiness itself; it is a category which is socially constructed, rather than a natural precondition or property of a borrower (Guba and Lincoln, 1994). A study of the predictive accuracy of an AI credit model that tacitly assumes a positivist ontology, for example, "creditworthiness" is an objective, measurable property that awaits discovery by a more powerful algorithm, has already answered this question, not just "before" but "before" any data are collected, in a particular way.

Theme 5: Ethical AI, Governance and Responsible Innovation

Explainable AI (XAI) research categorizes models into intrinsically interpretable models and post-hoc explanation techniques that are applied to more opaque "black-box" models. Fairness typically is measured through various measures such as disparate impact analysis, equal opportunity, and demographic parity. The governance literature has emerged from a

separate stream from the strategic management literature that has been reviewed. One widely observed and troubling finding in this literature is the presence of an "accuracy–fairness" trade-off: Fuster et al. (2022) demonstrate that machine-learning-based credit-scoring models can have larger differences between the performance of different demographic groups than conventional scoring methods and yet have higher overall accuracy. It partially stems from the fact that richer features used by the ML model can be an indirect proxy for characteristics that would otherwise be explicitly prohibited. While there is a long history of concerns about fairness, there is no consensus on a standard of fairness that is universally accepted and used in institutional and regulatory settings, and comparatively few studies that test and/or propose mitigation strategies for bias in credit-scoring models specifically. For instance, Kozodoi, Jacob and Lessmann (2022) demonstrate that various fairness-enhancing methods for credit scoring have materially different costs in terms of predictive profitability, and therefore, fairness and commercially viable are not necessarily compatible objectives; in addition, choosing between the fairness metrics is in itself a value-laden managerial choice, not merely a technical one — just the sort of managerial choice that the axiological analysis of Section 4.4 below argues is often not given the consideration it deserves.

The ethics mentioned in some of the above has been approached in a regulatory sense, which is correct but a more restricted interpretation of the literature. It is more accurate to separate the procedural ethics of informed consent, data protection, disclosure, from substantive ethics, distributive fairness, exclusion and the fundamental distribution of power between the institution that is developing an algorithm, and the borrower who is the subject of it. The majority of the studies reviewed here are fairly compliant with the aspects of procedural ethics (consent forms, privacy notices, anonymised data) and largely leave substantive ethics (who can question an automated lending decision, why) untouched. The most pointed ethical issues in this literature actually lie between procedural compliance and substantive accountability.

These worries are starting to be formalised by regulatory responses. For example, the EU's Artificial Intelligence Act defines artificial intelligence systems that assess consumers' creditworthiness as "high-risk" and sets the standards for transparency, man-in-the-loop and bias testing (European Parliament and Council of the European Union, 2024). With high-profile regulatory investigations, like the US regulators' action against algorithmic credit-limit-setting (HES FinTech, 2025), regulators are increasingly seeing 'the algorithm decided' as a weak justification for poor outcomes for customers. This is a special challenge for the emerging markets, where the alternative data that enables financial inclusion is the same as the data that can give rise to new, less explicit forms of bias – for example, mobile phone metadata might be highly correlated with a protected characteristic, such as gender, location, or ethnicity, even if the characteristic is not explicitly included in the data.

The focus is not on governance, either of the entire bank or fintech firm, or on who is responsible for fairness outcomes; it is on measuring fairness, quantifying it in metrics, and incorporating it into mitigation algorithms in a model, rather than on who in a bank or emerging-market fintech is responsible for ensuring fairness in its operations, how the governance role is distributed across data science, risk and compliance teams, and how "responsible AI" pledges are put into practice in the day-to-day decisions made by financial firms. This is another example of the procedural/substantive gap noted above: model-level metrics are a procedural safeguard, but do not address any substantive governance questions about who is responsible when a fair-on-average model results in an unfair individual outcome.

Theme 6: Literature synthesis and gaps in the research

This theme is NOT the final section of the literature review but rather is the intellectual culmination of the six themes above; it is the theme that brings the themes above together in the specific gap that the proposed doctoral research will address. This assessment combines the six themes above to produce an analysis of seven interconnected gaps. The overemphasis on predictive performance: Much of the research measures the impact of AI-supported personalisation by financial inclusion outcomes as a de facto and not a stated one, meaning that the outcomes are taken as given. Second, little organizational research: In the inclusion-outcome studies, little attention is paid to the organizational processes that led to the outcomes, while in the strategic management studies of digital transformation in banking, little explicit link between capability building and inclusion outcomes is made. Third, the literature on responsible-AI, especially, is technical and cast within a narrow, model-level lens, rather than one of organisations. Fourth, there are not many integrated frameworks in existence which include responsible-AI governance, technology adoption, and strategic-capability theory in a unified model that can be used for emerging-market lending.

Fifth, there is limited emerging-market evidence, compared with the number of papers based on North American and European experiences, and, within emerging markets, limited peer-reviewed evidence specifically from Pakistan, even though Pakistan is a large, underbanked emerging-market country with an existing fintech and microfinance sector. Sixth, and most fundamentally for this research, little philosophical discussion of the issue is found; the overwhelming number of studies reviewed take a positivist attitude, albeit implicit and unexamined, that does not appreciate the ontological and epistemological implications of such a perspective, nor the potential for other, complementary perspectives to be offered by a critical realist or pragmatist approach. Last, and most closely related to the absorptive-capacity perspective presented in Theme 3, very few of the studies examined examined how a bank's existing digital-infrastructure investment affects their capacity to implement AI-based personalisation and realise the resulting inclusion benefits, and to what extent. Finally, and most directly related to the absorptive-capacity perspective presented in Theme 3, very few of the studies examined touched on how a bank's existing digital-infrastructure investment

impacts their capacity to implement AI-based personalisation and the resulting inclusion benefits, and to what extent.

The seven gaps are shown in the synthesis matrix below in a column that covers all of them and can be read across one table instead of seven paragraphs, and are organised by theme.

Theme	What we know	What remains contested	Methodological / philosophical limitation	DBA research opportunity
1. Financial inclusion	Aggregate account-ownership gains are well documented	Whether access gains translate into meaningful, sustained use	Macro indicator studies rarely link to organisational process	Connect institution-level capability to borrower-level inclusion
2. AI personalisation	Alternative data widens the scoreable population	Whether widened access coexists with new exclusion via bias	Positivist, prediction-accuracy framing dominates	Examine access and exclusion as one mechanism, not two literatures
3. Strategic management	Multiple theories explain adoption and capability-building	Which theory, if any, explains inclusion specifically	Theoretically rich, empirically thin on inclusion	Integrate capability theory with inclusion outcomes
4. Research philosophy	Five philosophies are available and well theorised	Whether findings would differ under a different philosophy	Assumptions mostly implicit, rarely defended	Make philosophical choice explicit and consequential
5. Responsible AI	Procedural safeguards (consent, testing) are well established	Whether procedural compliance secures substantive fairness	Ethics treated as technical/model-level, not governance-level	Link responsible-AI governance to organisational accountability



6. Absorptive capacity & synthesis	Prior digital investment affects capability-building	Whether this explains variation in inclusion outcomes specifically	Rarely tested empirically in inclusion research	Test absorptive capacity as a driver of inclusion variation
------------------------------------	--	--	---	---

CHAPTER 4

Philosophical and Methodological Analysis

Study Overview

A TOE framework study on the impact of dynamic capabilities on digital transformation and innovation to enhance banking performance in the volume of 2024 published by Abdulrahman et al. in the Journal of Open Innovation: Technology, Market, and Complexity" was selected for detailed analysis. The project's stated objective is to examine the relationship between dynamic capabilities, as conceptualised in the Technology–Organisation–Environment (TOE) framework and the extent to which digital transformation and innovation outcomes in banking are affected. Methodologically, the authors employ questionnaires which are applied to 325 respondents of 48 banks in Indonesia. They then use partial least squares structural equation modelling (PLS-SEM) to analyse the data. The key finding of the study is that the dynamic capabilities, in turn, leverage organizational, technological and environmental dimensions to influence digital transformation, and thereby influence innovative and improved banking performance. The authors argue that a gap in the literature is the lack of integration of the TOE and dynamic capabilities theories in the banking industry, which they seek to remedy in this article.

Why this particular study was chosen over any other reviewed under Theme 3 is quite explicit, and that is because of two reasons: 1. The authors' exclusion of the study from the list of all those reviewed in the theme, and 2. The authors' selection of this particular study. It is, in the first place, the most dominant design methodology that could be identified throughout this theme, a theory-testing, quantitative, large-sample method, and, secondly, it is a non-representative (in the sense of not being a convenient or extreme case) study of digital transformation in the banking sector in an emerging market. Second, the organisational focus of this critique is close to the proposed doctoral research, which emphasizes capability-building, leading the limitations, in particular lack of attention to inclusion outcomes, to be carried over into the doctoral research's own interest in capability-building in Section 4.7 and 5.

It is worth noting that the choice of PLS-SEM and a TOE framework is itself notable, in fact, as it is a methodological combination that is used throughout the literature on digital transformation in banking reviewed in Theme 3. The choice of PLS-SEM in combination with a TOE framework is of note prior to the philosophical critique, as it is a methodological pairing that recurs throughout the literature on digital transformation in banking reviewed in Theme 3. PLS-SEM is widely used in this field due to its ability to address the non-normal distribution of most samples in organisational survey studies and to estimate multiple latent constructs and their interrelationships, which is suitable to test the multi-path model proposed by Abdurrahman et al. (2024). This popularity poses part of the issue identified by this research: if such a technique is selected because of its statistical convenience when only a small number

of organisations are involved, then it is by default the preferred method for the field to answer questions about digital transformation – limiting the range of research designs and findings that a field can produce as a whole.

Ontological Analysis

The study adopts an ontological approach to the concept of organisation, in which the constructs such as "dynamic capability," "digital transformation" and "banking performance" are assumed to be objective characteristics of a bank that can be measured through a structured survey tool administered to certain respondents. This is the ontological perspective of the objectivists; they see the organisation as being "out there" already rather than as emerging from and being shaped by the daily practices of bank workers, and they imagine that its reality can be measured by using the right surveys and the right items. The study's objectivist framing precludes, but doesn't test, whether those who are respondents in the same bank have meaningfully different "situated" understandings of what "digital transformation" means in their context and specific role.

Epistemological Analysis

The epistemology of the study must be more clearly specified than just "positivist", as a quantitative design does not necessarily mean a strict positivist epistemology. There are two candidate readings, and the authors of the study don't actually state which one they believe it supports.

Its production is strictly positivist, in the sense that it is achieved by testing in advance the hypothesis of relationships between digital transformation, dynamic capabilities, and banking performance, based on validated scales of measurement and structural equation modelling, to determine the significance and strength of the paths proposed in the model, it being assumed that a correctly specified model is able to capture an objective reality. The procedures are better interpreted, instead, as a proxy for that reality, rather than a direct observation of it, and as such are viewed as probabilistic and error prone, consistent with the use of validity and reliability testing as a hedge against measurement error in this study. The study's own practice tends towards the post-positivist reading, inasmuch as validity and reliability testing assumes that the measurement is imperfect, but this distinction cannot be discerned from a declaration of the philosophical stance, it must be read out from the methodological choices, which the authors do not explicitly declare and therefore read with caution, rather than in absolute terms.

Axiology and Researcher Positionality

The study does not explicitly report on the positionality, values or ethical stance of the researchers, as in positivist tradition, which puts a premium on the impartiality and distance of the researcher from the phenomenon under study. In this study, it can be said that an axiological position has been taken, meaning that the research authors' view on what constitutes 'improved banking performance' or 'successful' digital transformation is accepted

as the norm, and not foregrounded or challenged. This silence is axiologically significant in and of itself, in that it appears as findings that are value-free statistical outputs.

The axiological question this critique brings up is not as stark as the one that has been raised already – success for whom? The concept of improved banking performance could be interpreted in terms of shareholders' return on capital (profitability), the performance of the bank (operational efficiency), regulators (stability and compliance), SME and consumer borrowers (better terms, faster response) or previously unserved borrowers (whether reached or not). The survey instrument used in this study is tailored to the bank employee and privileges the first three perspectives and does not include any way to capture the last two in the structure. Assumptions of what is 'improved performance' are not neutral, making this silence a more significant constraint on research specifically focused on responsible innovation and financial inclusion than it would be for other more narrowly technical research.

Methodological Quality

Some methodological strengths of the study include the use of an established analytical technique well suited for complex models containing multiple latent constructs, the fairly large sample size (325 respondents from 48 banks) and the assumed "standard" reporting of validity (convergent and discriminant validity) and reliability (e.g., Cronbach's alpha, composite reliability) statistics consistent with the PLS-SEM reporting tradition. The weaknesses of this type of survey research are cross-sectional design which fails to capture the hypothesized causal sequence, a single country banking sample (Indonesia) that restricts generalizations to other emerging-market contexts, such as Pakistan, and the use of self-reported perceptual measures of constructs such as "dynamic capability," which can lead to common-method bias and social-desirability effects.

It is also noteworthy what the study does not report, because the absence of it is informative for a methodological critique: there are no indications of measures that were taken to reduce common method bias in the study design, e.g., a temporal or a procedural separation of predictor and outcome measures, nor any sensitivity analysis testing the robustness of the path coefficients to alternative specifications. Both omissions are not uncommon in this type of study, and both would require consideration before claims of such an integration of capability building and inclusion outcomes could be considered as credible informing the doctoral research.

Reliability and validity are considered separately below, rather than as one general issue because the two have different implications for the results of the study that can be drawn from it.

Issue	Strength	Limitation	Implication for findings	Alternative design
-------	----------	------------	--------------------------	--------------------

Construct validity	Convergent/discriminant validity presumably reported per PLS-SEM convention	Latent constructs (e.g. "dynamic capability") remain researcher-defined abstractions	Findings depend on whether the construct matches practitioners' lived understanding	Qualitative pre-study to ground construct definitions
Internal validity	Structured, validated survey instrument	Self-reported, single-source data invites common-method bias	Path coefficients may overstate true relationships	Multi-source data (e.g. performance records plus survey)
External validity	Reasonably large sample (325 respondents, 48 banks)	Single-country (Indonesian) sample	Limited generalisability to Pakistan or other emerging markets	Comparative multi-country replication
Cross-sectional causality	Model specifies a plausible causal sequence	Cross-sectional design cannot establish temporal ordering	Reported "effects" may be correlational, not causal	Longitudinal or panel design
Sampling / common-method bias	Sampling frame spans multiple banks	No stated procedural separation of predictor/outcome measures	Reported associations may be inflated by shared method variance	Temporal or multi-rater separation of measures

Ethical Considerations

In contrast to the more pressing ethical issues (algorithmic fairness, consumer privacy, explainability to end-borrowers) that emerge in studies looking at AI models applied directly to consumers, as reviewed under Theme 5, the ethical considerations in this survey-based organisational study are rather conventional: informed consent, confidentiality, and voluntary participation of respondent bank employees. That is not a mere coincidence but is a direct result of the ontology and axiology of the study examined above: since the study does not consider the two terms "dynamic capability" and "banking performance" to be constructs that have distributive consequences for borrowers, it never has to enter the harder ethical space that the algorithmic study of the object of study itself brings with it — accounting to loan recipients for the consequences of that algorithm. This reflects the need identified in Theme 6 to develop strategic management research and responsible-AI research.

The bifurcation has a practical implication for the proposed doctoral design. A study that, like this study, aims to link variables of an organisation's capabilities to outcomes at the borrower level will probably have to meet two types of institutional ethics review, one the relatively routine employee-survey type, and a second data-protect, data consent, and algorithmic transparency type if borrower-level or credit-decision data are being used. It is a methodological choice, one that is rarely explicitly addressed in the reviewed literature, because they don't consider this dual requirement when they think about the proposal.

Critical Appraisal

As a suitable method and a technique that is becoming more common in this type of organizational research, the strength of the study conducted by Abdurrahman et al. (2024) is that it tests a model that is theoretically sound and well-defined in a quantitative manner from a realistic perspective. This is its key constraint and the takeaway from this section: Banking performance and digital transformation are for themselves; not necessarily outcomes of financial inclusion for previously un-served SME and consumer segments. The study can then conclude that there is an association between dynamic capabilities and general performance improvement but cannot conclude whether that association is in the form of more inclusive lending or not, which is more important than it may seem at first sight and where the term “capability” can be confused with “inclusion” in the broader literature. Linking capability building to inclusion outcomes, as is the primary focus of the proposed doctoral research, would be better served by a different approach, such as a mixed-methods case study methodology that integrates qualitative interviews with managers who make lending decisions using AI tools with survey data, or a longitudinal design that measures inclusion outcomes over time alongside capability outcomes. The only conclusion of Section 4 that most clearly affects the methodological aspect of the doctoral research, which will be developed in section 5, is this capability/inclusion distinction.

CHAPTER 5

Discussion and Contribution

Combining the critical literature assessment with an analysis of the question(s) that the research aims to answer can address the main question of the research: How does research philosophy influence AI-enabled financial inclusion research? Evidence clearly shows a trend. Most of the literature has a positivist or post-positivist epistemology, it is either one that assumes technical performance or organisational capability is a measurable property and is oriented towards predicting credit-scoring performance or at organisational capability building, respectively, or one that treats both as such without its epistemology being examined. The latter is arguably an important decision in terms of the possibility of whether or not AI personalisation will actually help to progress inclusion, but it's also a philosophical choice that consistently shifts the focus of research on what can be measured (accuracy, statistical path coefficients) and not on what can't (managerial sense-making, borrower experience of algorithmic decisions, the lived reality of financial exclusion). Whereas this pattern is more problematic than just a lack of coverage, as it demonstrates that the primary strategies in the field are subtly shaping and determining, ahead of time, what counts as evidence of inclusion.

This discussion gives rise to three contributions, which are left separate from each other, rather than being folded into one another.

Theoretical contribution: An integration of the three theories—strategic-capability, financial-inclusion, and responsible-AI governance. While the comparison table in Theme 3 highlights how Dynamic Capabilities and the RBV can account for organisational capability-building, they do not account for outcomes for inclusion or explain ethics in AI-governance; and responsible-AI frameworks explain outcomes for fairness and explainability, but not for organisational and inclusion-level dynamics; TAM explains individual AI-adoption, but not organisational and inclusion-level dynamics. But none of these three is integrated in a single existing framework; the proposed doctoral research is to treat the integration as its own theoretical contribution, though, as the paragraph below on limitations indicates, the integration is not taken for granted, but rather is an open research question.

Mixed methods methodological contribution: The mix of organisation-level evidence (capability indicators, governance structures) with borrower-level evidence (inclusion outcomes, lived experience of algorithmic decisions) is what Section 4 highlights as the sting in the tail of the dominant mono-method quantitative designs in this field.

Practical contribution: A governance framework for responsible AI-enabled lending that banks, fintech companies and emerging-market regulators can use to discuss capability-building, philosophical clarity about what is being measured, algorithmic fairness auditing and

responsible-AI governance, as a clear checklist, rather than going with whichever of the four is being highlighted by a vendor's marketing material.

Before moving on to methodology, it is important to note one problem with this argument. Creating an integrated theoretical framework is easier said than done: Each one of these theoretical frameworks (Dynamic Capabilities, the RBV, TAM and responsible-AI governance) addresses a specific set of questions, such as what is being analysed (the level of entity, the organisation, the individual, the algorithm), which unit of analysis (the organisation, the individual, the algorithm), and with which implicit philosophy (dynamic capability, RBV, TAM and responsible-AI governance). They may be used together in a way that results in either a superficial checklist that uses terms from each concept without any real theoretical connection, or a cumbersome model that is not easily tested empirically. The proposed doctoral study should ask not only what an integrated framework should include, but also whether it is reasonable to expect to be able to do something meaningful in an integrated manner across these philosophically different traditions, or whether it is more reasonable to only expect to be able to contribute in an explicitly bridging way, and in an explicitly empirical manner.

The key message from this conversation is for a Pakistani bank or fintech company to not wait until the academic system is fully connected before taking action. Instead, it is to consider these four elements here as a minimum list to be worked through - on purpose - when an AI-powered lending platform is being procured or developed internally. This is an important distinction between an academically sound structure and a practically adequate checklist that is transferable to practice from this research.

Here, the adoption of pragmatism is not due solely to the fact that it allows for mixed methods, which is enough at DBA level. It is adopted due to its ontological, epistemological and axiological foundations being particularly suitable for this research problem. Pragmatism does not pre-judge ontology, that is whether there is an objective reality or a constructed reality; it does not a priori assume that the nature of a 'dynamic capability' or of an 'inclusion' is objective or constructed reality, but rather makes it an empirical issue to be explored. Epistemologically, it embraces both knowledge of measurable inclusion outcomes (which is necessary to demonstrate the inclusion outcomes at banks at the statistical level) and knowledge of managerial and governance sense-making (which is necessary to explain how managers and governors make sense of inclusion). On the axiological level, pragmatism is clear that values of the researcher influence the type of research problems that are considered, the questions that are asked and the outcomes that are deemed significant — a point that is directly continued from the axiological critique presented in Section 4.4, which highlighted the unspoken question of "success for whom?" as a main limitation of the purely positivist design.

This philosophical stance is reflected in a methodological sequence, which is research problem, philosophical position, methodology, methodology: methods, evidence,

contribution. A research problem (does capability-building translate into inclusion, and under what governance conditions?) motivates a pragmatist position; pragmatism motivates a mixed-methods methodology; the latter is then operationalised by quantitative analysis of lending and inclusion indicators and qualitative interviews with managers responsible for deploying AI-driven personalisation; the resulting evidence is then generalisable and contextually grounded; and the contribution is the integration set forth above, namely the theoretical, methodological and practical integration.

There are three types of mixed methods design: explanatory sequential design in which quantitative phase is used to measure the capability and inclusion indicators; exploratory sequential design in which quantitative phase is used to seek information to supplement the results of the qualitative phase; convergent design (Saunders, Lewis and Thornhill, 2023) in which the quantitative and qualitative phases are conducted simultaneously (Saunders, Lewis and Thornhill, 2023). The proposed doctoral research is explanatory sequential design in which quantitative phase is used to collect data to measure capability and inclusion indicators across a sample of Pakistani banks and then qualitative phase is conducted to explain the results of the quantitative phase, which are unexpected or ambiguous. This is preferred over a convergent design because it would allow the qualitative phase to measure whatever was left unmeasured in the quantitative phase, and not have to follow an exploratory sequential design because there is a lot that is already known about which capability and inclusion constructs to measure in the quantitative phase from the outset.

For instance, a pragmatist approach would allow data from Pakistani banking institutions regarding the level of lending and inclusion indicators to be analyzed quantitatively, and for managers responsible for the deployment of AI-driven personalisation, to conduct qualitative interviews that would produce generalisable patterns of data combined with explanatory data from the context. The post-positivist alternative is defensible in that this research has fewer sub-questions that demand more tightly controlled hypothesis testing, and is less well suited to the general aim of the research of interrogating the research's own philosophical assumptions reflexively, which a purely post-positivist design would not be able to hold up to its own questioning.

CHAPTER 6

Conclusion

This research critically examines the literature on AI-driven personalisation and financial inclusion in SME and consumer lending, however, not just as a technical field but also by placing it within the context of the underlying philosophy of the literature. There are three lessons here to keep in mind. Conceptually, the literature is predominantly positivist (although sometimes implicit) which has resulted in a research tradition that has focused more on prediction of performance and less on understanding of organisations, management and ethics. Methodologically, mono-method quantitative designs (such as the case of the close analysis carried out by Abdurrahman et al. 2024) render the process of translating organisational capability-building into outcomes of inclusiveness for previously unserved borrowers open to significant discussion, which is better addressed in mixed-methods approaches. While none of the current frameworks – Dynamic Capabilities, the RBV, TAM, or responsible-AI governance models – fully describes AI-driven financial inclusion as a strategic, organisational and ethical phenomenon, there is a potential for an integrated framework to do so.

The conclusion is not reiterated extensively here, but instead consists of three statements.

What the literature reveals: AI-powered personalisation can increase the number of borrowers the bank can score, and the strategic capability theory of organisations provides a reasonably robust explanation of how banks can develop the capability to utilize AI.

What it can no longer prove: that such expanded access, or the ability to organize it, delivers enduring and substantive financial inclusion for previously unincluded borrowers; that is what Abdurrahman et al. (2024) in Section 4 make clear, and Theme 6's synthesis matrix reveals that it remains true across the entire literature.

The manner in which the proposed research seeks to fill that gap: The proposed doctoral research is an intentionally designed pragmatic, explanatory sequential mixed methods study that seeks to link evidence of organizational capability to the outcomes of inclusion at the borrower-level in the context of SME and consumer lending in Pakistan, rather than assuming that organizational performance is a proxy for borrower-level inclusion, as many of the reviewed studies do.

Finally, organisational capabilities and financial inclusion are not the same thing, and when they are used interchangeably, whether explicitly or implicitly, by simply failing to differentiate between them, it is more of a philosophical decision that will have consequences for practice than a neutral simplification, as detected by the critical analysis made by Abdurrahman et al. (2024). The literature review presented here needs to be followed by future research that focuses on longitudinal study designs to determine whether gains in

inclusion generated by the use of AI in financial services persist over time, on comparative study designs across emerging-market regulatory regimes, and on designs that explicitly draw connections between capability building and measurable, borrower-level inclusion outcomes in financial services, closing the gap identified in this review between the scholarship in strategic management and the responsible and inclusive deployment of AI in financial services.

References

- Abdurrahman, A., Rosiello, A., Lasrado, L. and Yasin, M. (2024) 'Impact of dynamic capabilities on digital transformation and innovation to improve banking performance: A TOE framework study', *Journal of Open Innovation: Technology, Market, and Complexity*, 10(2), 100215. Available at: <https://doi.org/10.1016/j.oiotmc.2024.100215>
- Alharahsheh, H.H. and Pius, A. (2020) 'A review of key paradigms: positivism VS interpretivism', *Global Academic Journal of Humanities and Social Sciences*, 2(3), pp. 39–43. Available at: <https://www.gajrc.com/articles/87/>
- Barney, J. (1991) 'Firm resources and sustained competitive advantage', *Journal of Management*, 17(1), pp. 99–120. Available at: <https://journals.sagepub.com/doi/10.1177/014920639101700108>
- Bhaskar, R. (1975) *A Realist Theory of Science*. Leeds: Leeds Books.
- Cohen, W.M. and Levinthal, D.A. (1990) 'Absorptive capacity: A new perspective on learning and innovation', *Administrative Science Quarterly*, 35(1), pp. 128–152. Available at: <https://doi.org/10.2307/2393553>
- Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, 13(3), pp. 319–340. Available at: <https://misq.umn.edu/misq/article-abstract/13/3/319/191/Perceived-Usefulness-Perceived-Ease-of-Use-and?redirectedFrom=fulltext>
- DiMaggio, P.J. and Powell, W.W. (1983) 'The iron cage revisited: institutional isomorphism and collective rationality in organizational fields', *American Sociological Review*, 48(2), pp. 147–160. Available at: <https://www.jstor.org/stable/2095101?origin=crossref>
- European Parliament and Council of the European Union (2024) Regulation (EU) 2024/1689 Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act). Brussels: Official Journal of the European Union
- Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T. and Walther, A. (2022) 'Predictably unequal? The effects of machine learning on credit markets', *The Journal of Finance*, 77(1), pp. 5–47.
- Guba, E.G. and Lincoln, Y.S. (1994) 'Competing paradigms in qualitative research', in Denzin, N.K. and Lincoln, Y.S. (eds.) *Handbook of Qualitative Research*. Thousand Oaks, CA: Sage, pp. 105–117.
- HES FinTech (2025) AI in Lending: AI Credit Regulations Affecting Lending 2025. Available at: <https://hesfintech.com/blog/all-legislative-trends-regulating-ai-in-lending> (Accessed: 3 September 2026).
- International Finance Corporation (2025) G20 Global Partnership for Financial Inclusion: Action Plan for MSME Financing. Washington, DC: IFC.

Kshetri, N. (2021) 'The role of artificial intelligence in promoting financial inclusion in developing countries', *Journal of Global Information Technology Management*, 24(1), pp. 1–6. Available at: <https://www.tandfonline.com/doi/full/10.1080/1097198X.2021.1871273> (Accessed: 26 August 2026)

Kozodoi, N., Jacob, J. and Lessmann, S. (2022) 'Fairness in credit scoring: Assessment, implementation and profit implications', *European Journal of Operational Research*, 297(3), pp. 1083–1094. Available at: <https://arxiv.org/abs/2103.01907>

Raza, M., Wahab, R.A. and Madad, A. (2026) 'Artificial intelligence–driven financial inclusion and green entrepreneurship: examining the role of digital lending platforms in promoting sustainable SME growth in Pakistan', *Advance Journal of Econometrics and Finance*, 4(2), pp. 996–1006.

Saunders, M., Lewis, P. and Thornhill, A. (2023) *Research Methods for Business Students*. 9th edn. Harlow: Pearson. Available at: <https://www.pearson.com/en-gb/subject-catalog/p/research-methods-for-business-students/P200000010080/9781292402727>

Vial, G. (2019) 'Understanding digital transformation: A review and a research agenda', *Journal of Strategic Information Systems*, 28(2), pp. 118–144. Available at: <https://doi.org/10.1016/j.isis.2019.01.003>

World Bank (2025) *The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy*. Washington, DC: World Bank.

World Bank Group (2025) *SMEs Finance*. Available at: <https://www.worldbank.org/en/topic/smefinance> (Accessed: 15 September 2026).