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ARTIFICIAL INTELLIGENCE AS A CALL FOR RETAIL BANKING: APPLYING DIGITAL OPTIONS THINKING TO ARTIFICIAL INTELLIGENCE ADOPTION

Research Paper

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Abstract

Technology-driven challenges, both existing and emerging, require banks to invest in IT capabilities, especially in artificial intelligence (AI). Digital options theory presents a valuable guide rail for these investments. However, the nature of AI as a moving frontier of computing requires certain extensions to established digital option thinking. Based on interviews with 23 experts in the retail banking industry, we highlight the importance of thinking broadly when laying the foundation for AI options and being mindful of the dynamic effects of contextual factors. Drawing from digital options theory and the Technology-Organization-Environment framework as dual lens, our study adds a structured approach to consciously balance resources and AI-related capability investments with a broader consideration of the banking industry's complex environment. In this way, our study complements recent research on the interplay between incumbents' resources and digital opportunities.

Keywords: Artificial Intelligence, Digital Options, Retail Banking, Technology-Organization-Environment Framework.

1 Introduction

These are challenging times for retail banks (Vives, 2020). FinTechs, non-, and near banks threaten to disrupt established industry structures and dynamics, and force banks to adapt their processes and services (Chen et al., 2017). Simultaneously, banks must cope with extensive new regulations like the Payment Services Directive 2 (PSD2) that force them to open their systems and make their IT infrastructures more reliable (Botta et al., 2018). Moreover, customers increasingly ask for digital services. While the global size of the online banking market was \$11.43 billion in 2019, it is expected to hit \$31.81 billion by 2027 (Chhabra et al., 2020).

Most of these challenges require banks to heavily invest in new IT capabilities (Du, 2018; Panda and Rath, 2017). With the increasing impact of IT on business-level strategies (Drnevich and Croson, 2013), banks need to understand how to successfully manage these investments. Investments in

artificial intelligence (AI) are a case in point. New entrants like Alibaba, Alphabet, and Apple, rely heavily on AI applications such as robo-advisory to compete with incumbent retail banks (Belanche et al., 2019). While these new entrants struggle to get hold of training data, banks have ready access to customer transaction data, including spending habits, contract fees, and income. This data provides considerable potential to lower operational costs and add business value through a better customer experience (Königstorfer and Thalmann, 2020). In that way, banks' existing resources not only constrain but also enable digital opportunities like AI applications (Oberländer et al., 2021).

However, retail banks have only recently started experimenting with AI and are struggling considerably (Belanche et al., 2019). Common challenges are due to the complexity of the environment (e.g., sensitivity of data or regulatory pressure) and include inert legacy systems and compliance requirements (Sia et al., 2016). Moreover, AI-enabled systems' ability to perform cognitive functions previously reserved for humans may require a re-examination of existing IS concepts (Benbya et al., 2021; Rai et al., 2019). Identifying relevant use cases is also often difficult because AI is a general-purpose technology rather than an application (Agrawal et al., 2019; Jöhnk et al., 2021). Moreover, the nature of AI as a dynamic frontier that moves with advancements in computing forces managers to continuously adapt and explore possible AI use cases, business value, and strategic fit (Berente et al., 2021).

Methods for use case identification (Hofmann et al., 2020) can help banks navigate some of these challenges. They are not enough, however, to guide strategic investments in AI-related IT capabilities. These investments rather require informed CIOs and boards of directors (Li et al., 2021) as well as organizational readiness (Jöhnk et al., 2021). Moreover, they require a strategic frame that combines a technical, managerial, and temporal perspective (Raisch and Krakowski, 2021). Incumbent banks thus need means to structurally evaluate investments in AI-related capabilities to seize opportunities from their existing resources (Oberländer et al., 2021) while addressing potentially unintended adverse outcomes (Benbya et al., 2020) that may lie in AI's inscrutability (Asatiani et al., 2021; Teodorescu et al., 2021) or flawed ground truth assumptions in training and evaluating AI models (Lebovitz et al., 2021). Against this backdrop, we ask the following research question:

How can banks successfully manage their investments in AI-related IT capabilities?

To answer this question, we employ digital option theory as our theoretical lens (Sambamurthy et al., 2003; Sandberg et al., 2014; Svahn et al., 2015). Digital options provide a mental model for organizations to think about IT capability investments without having to realize them (Rolland et al., 2018). The digital options lifecycle provides additional guidance for the identification, development, and realization of IT investment opportunities. In this way, digital options thinking allows to incorporate considerations about future investments in AI-related IT capabilities into business-level strategizing. Although powerful, the digital options frame has certain limitations when applied in isolation. Digital options thinking typically focuses on how internal information requirements, process performance, and digital options interact in an organizational context; external factors are treated as exogenous factors of subordinate interest (Rolland et al., 2018; Sambamurthy et al., 2003). AI adoption, on the other hand, requires actively monitoring these factors and making highly context-specific decisions (Jöhnk et al., 2021). We thus draw on a complimentary Technology-Organization-Environment (TOE) lens (Tornatzky and Fleischer, 1990) to also include external factors and their effects on the digital options lifecycle. This dual lens balances focus on the organization-level challenges that retail banks face in their efforts to adopt AI with a broader consideration of the industry's complex environment. In this way, our study also complements recent research on the interplay between incumbents' resources and digital opportunities (Oberländer et al., 2021).

To answer our research question, we conduct an interview study (Schultze and Avital, 2011) and analyze interview data from 23 experts who engage with AI in the retail banking industry. We apply open and axial coding techniques to identify emerging themes and relationships from the interview data (Corbin and Strauss, 1990) and further develop our conceptualization with insights from the digital options literature as well as insights from existing practitioner studies (Flick et al., 2010). The results of our analysis offer insights into the generation of AI options in retail banking and the effect of

TOE factors on the lifecycle of these options. We conclude with a discussion of our findings, pointing out our contributions, the limitations of the paper, and future research possibilities.

2 Literature background

2.1 Artificial intelligence

Artificial intelligence (AI) is not a new concept; it was first introduced in the 1950s at the intersection of computer science, psychology, and cognitive science (Simon, 1995). Early AI research focused particularly on the concept of intelligence and the capabilities of computers to perform intelligent tasks. As progress in computational capabilities was slow, initial interest soon subsided. Yet, interest quickly rebounded once AI algorithms became viable in practice (Stone et al., 2016). Bolstered by high data availability, computational power, and increased processing speed, AI has today become a crucial topic for companies and governments. Driven by these developments, regulators are also increasingly weighing in on AI. The European Commission, for instance, sees an urgent need for a regulatory framework that reigns in potential risks of AI and prevents its use for malicious purposes (European Commission, 2020). Investing in AI thus requires not only identifying its opportunities but also mediating its risks and navigating a dynamic and uncertain regulatory environment.

Due to the long history of AI, researchers have introduced multiple definitions. We understand AI as “the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, learning, and interacting with the environment, problem-solving, decision-making, and even demonstrating creativity” (Rai et al., 2019). It is this ability to perform cognitive functions and to rival human capabilities that may require a re-examination of various IS concepts in the realm of AI (Benbya et al., 2021; Rai et al., 2019). To name but one example, AI can facilitate organizational learning in turbulent environments (Sturm et al., 2021), but its complexity can also introduce unintended adverse outcomes (Benbya et al., 2020), such as substantial challenges to fairness (Teodorescu et al., 2021) or potential conflicts to employees’ professional role identity (Strich et al., 2021). It is, therefore, unlikely that AI will simply fit into prevailing concepts for the management of traditional IT, nor is it self-evident how its wider use will affect innovativeness and competitive advantage (Benbya et al., 2021; Vial, 2019). At the same time, AI is understood as a dynamic frontier that moves with advancements in computing technologies (Berente et al., 2021). Consequently, managers need to continuously adapt their roles to remain informed and understand relevant facets of AI. Moreover, organizations need means to dynamically assess AI and investments in AI-related IT capabilities from both technical and managerial perspectives (Raisch and Krakowski, 2021). In particular, successful implementation requires understanding and managing AI readiness in light of context-specific factors (Jöhnk et al., 2021).

Yet, research on AI in (retail) banking is often limited to investigations of social and economic implications of its adoptions. Examples include the impact of AI on jobs in the banking industry (Jakšič and Marinč, 2019) or the (efficiency) impact of AI on specific processes such as anti-money laundering, high-frequency trading, or chatbots (Donepudi, 2017; Kaya, 2019). Our research aims to bridge this gap and investigate how investments in AI capabilities can become an integral part of business strategies in retail banking.

2.2 Digital options theory

IS research offers various theories and models to investigate the adoption of AI, ranging from diffusion of innovation theory (e.g., Alsheibani et al., 2018) to affordance-experimentation-actualization theory (e.g., Keller et al., 2019). These models and theories are powerful at explaining the intention to adopt and discovering action possibilities associated with AI. Yet, they offer little guidance for incumbent practitioners on how to capitalize on their resources and create competitive opportunities from AI (Oberländer et al., 2021). Digital options theory can address this issue.

The theory is rooted in financial research, where options represent possibilities to realize an investment opportunity in the future and gain an advantage by realizing the investment (Black and Scholes, 1973). Over the years, options thinking has also found its way into management research. An organization's investments in resources such as its capabilities and assets can be conceptualized as a 'real' option that provides the organization with opportunities for future strategic actions that the organization can realize when the conditions are right (Bowman and Hurry, 1993). Financial and real options thinking and the corresponding financial valuation models have also found their way into IS, and real options analysis (ROA) is a well-established method to evaluate IT investments (Ullrich, 2013). However, applying these methods to digital options in general and new technologies in particular can be difficult because important model assumptions (e.g., a complete market or certain cashflows) are often not applicable in these contexts and require sometimes artificial work-arounds such as simulation-based approaches (Müller et al., 2016; Ullrich, 2013).

At the same time, digital options thinking provides value beyond quantitative valuation (Fichman et al., 2005). It can help managers develop opportunities for IT capability investments without the obligation to pursue them, choose from available options, and electively carry out these investments (Sandberg et al., 2014). Analogous to the financial option lifecycle, managers can follow a process of (1) identifying, (2) developing and (3) realizing digital options (Sandberg et al., 2014, Svahn et al., 2015, Rolland et al., 2018). These process steps constitute crucial transformations in the life of a digital option and make it [1] available, [2] actionable, or [3] realized respectively (Sandberg et al., 2014). Available options are investments opportunities that are waiting to be identified. Once organizations have identified these opportunities, they can evaluate and develop their desirability and feasibility to make them actionable. Selected actionable options can then be 'realized' or 'activated' through a larger investment in the required IT capabilities (Sandberg et al., 2014). In effect, digital options theory provides a useful strategic means to conceptualize and prepare future IT capability investments (Oberländer et al., 2021).

Within the context of AI, digital options can be understood as potential, future AI applications that firms can make possible by investing, for instance, in AI-ready IT infrastructure. Such foundational investments increase the value proposition of later AI applications (Rolland et al., 2018) and enable the development of actionable AI options. To create actionable AI options, however, organizations must first identify available options. Second, they have to evaluate and develop these options for feasibility and desirability. In a third step, they can realize them by selectively implementing AI applications into an organization's infrastructure and work processes (Sandberg et al., 2014).

Digital options theory has been applied primarily to established IT systems, such as enterprise resource planning systems (Sandberg et al., 2014) and digital platforms (Rolland et al., 2018). Yet, it can also be useful for emerging technologies (Svahn et al., 2015). While early research was strongly concerned with an intra-organizational perspective, Sandberg et al. (2014) and Svahn et al. (2015) have opened the door for contextual factors, such as industry trends, product settings, innovation vision, and technological and organizational resources (Svahn et al., 2015). Yet, digital options theory still lacks a systematic conceptualization and reflection of the dynamic impact of these factors.

2.3 The Technology-Organization-Environment framework

IS research offers many different frameworks to examine the influence of contextual factors on technology adoption. We chose to focus on the TOE framework, as it has already informed several studies on AI adoption (e.g., Alsheibani et al., 2018; Jöhnk et al., 2021). As its name suggests, the TOE framework describes the adoption process in terms of the impact of the technological context, organizational structures, and environmental factors (Tornatzky and Fleischer, 1990).

The *technological context* includes relevant technologies available and applicable to the organization, either in the market (e.g., through service providers) or internally (Baker, 2012). Moreover, it covers the organization's current infrastructure, which determines the readiness for new technologies (Zhu et al., 2004). The *organizational context* covers factors like the organization's size and slack, internal centralization and formalization, and the impact of these factors on the innovation phase (Baker,

2012). *Environmental factors* encompass competitors, industry characteristics, and government involvement (e.g., regulation) (Baker, 2012; Zhu et al., 2004). Contextual factors exert influence on technology adoption and are interdependent (Zhu et al., 2006). For instance, top management support (organization) impacts technological readiness (technology), and environmental factors such as regulation determine how top management invests in technological readiness.

Researchers have applied the TOE framework to a broad range of adoption processes, such as e-business (Zhu et al., 2006), business process standards (Venkatesh and Bala, 2012), enterprise resource planning software (Awa et al., 2016), or cloud computing (Borgman et al., 2013). Examples also exist for the banking industry (Riyadh et al., 2009) and AI adoption outside the banking industry (see Table 1). Drawing on both digital options theory and the TOE framework allows us to better understand the incorporation of AI-related IT capability investments in business-level strategies, while considering the dynamics of exogenous as well endogenous factors along their life cycle.

Technology	Organization	Environment
<i>Relative advantage</i> (Alsheibani et al., 2018; Pillai and Sivathanu, 2020)	<i>Top management support</i> (Alsheibani et al., 2018, 2019; Demlehner and Laumer, 2020; Mahroof, 2019; Pillai and Sivathanu, 2020)	<i>Competitive pressure</i> (Alsheibani et al., 2018; Demlehner and Laumer, 2020; Mahroof, 2019; Pillai and Sivathanu, 2020)
<i>Existing (IT) infrastructure</i> (Alsheibani et al., 2018, 2019; Mahroof, 2019; Demlehner and Laumer, 2020)	<i>Resources</i> (Alsheibani et al., 2018, 2019; Demlehner and Laumer, 2020)	<i>Regulation</i> (Alsheibani et al., 2018, 2019; Demlehner and Laumer, 2020)
<i>Security and privacy</i> (Alsheibani et al., 2019; Pillai and Sivathanu, 2020)	<i>Expertise</i> (Alsheibani et al., 2019; Demlehner and Laumer, 2020; Mahroof, 2019)	<i>External availability of AI</i> (Demlehner and Laumer, 2020; Pillai and Sivathanu, 2020)
<i>Cost-effectiveness</i> (Demlehner and Laumer, 2020; Mahroof, 2019; Pillai and Sivathanu, 2020)	<i>Change management</i> (Alsheibani et al., 2019; Demlehner and Laumer, 2020; Mahroof, 2019; Pillai and Sivathanu, 2020)	
	<i>Size</i> (Alsheibani et al., 2018; Demlehner and Laumer, 2020)	

Table 1. TOE factors that impacting AI adoption as identified in the literature.

3 Research approach

We applied a qualitative research approach to examine how banks manage investments in AI-related IT capabilities. A qualitative approach is particularly helpful if a concept or phenomenon is still comparatively new, or little is known about its manifestation in certain contexts (Creswell, 2014). While the concept of AI is not new, insights about its application in many industries are still scarce. The qualitative approach helped us to develop a deeper understanding of the adoption of AI in specific context of banking and account for the complexity banks had to face in aligning their resources with AI-related IT capability investments.

3.1 Data collection

To better understand how retail banks managed their investments in AI-related IT capabilities and the impact of context factors on the digital options lifecycle, we conducted an in-depth interview study. We used purposive sampling to identify 23 AI experts within the banking industry in German-speaking countries who are directly or indirectly involved in adopting AI. We selected these experts based on a high level of industry knowledge (banking) and knowledge of AI. Moreover, we looked for

experts with decision-making authority, that is, experts with strategic positions in their companies or considerable liberties in AI projects. This approach allowed us to holistically explore digital options in the German-speaking, retail banking industry and the impact of organizational context. We conducted the interviews between February 2020 and July 2020, mostly with bank and FinTech management and service providers, such as data centers, and stopped data collection after 23 interviews as themes were increasingly repetitive and no new topics emerged.

Company	Interviewee	Role
Bonus Program	I01	Founder
Direct Bank I	I02, I03	Division Manager, Division Manager
Direct Bank II	I04	CIO
Financial Advisory	I05	CIO
FinTech I	I06	Co-Founder
FinTech II	I07	Co-Founder
FinTech III	I08	CEO
FinTech IV	I09	Founder
FinTech Hub	I10	Co-Founder
IT Service Provider I	I11, I12, I13	Data Scientist, Founder, CPO
IT Service Provider II	I14	Division Manager
IT Service Provider III	I15	Country Manager
IT Service Provider IV	I16, I17	Partner, Partner
Specialist Bank I	I18	Data Scientist
Specialist Bank II	I19	Co-CEO
Universal Bank I	I20, I21	CIO, Managing Director
Universal Bank II	I22	Retail Manager
Universal Bank III	I23	Retail Manager

Table 2. Interviewees and their role within their respective companies.

The interviews were semi-structured and based on interview guidelines. We began each interview with an introduction that provided the interviewee with necessary context information about ourselves and the research project. The interviewees then briefly discussed their relevant backstory, personal experience, and pertinent experiences with AI in the banking industry. The introductory part also included establishing a shared understanding of the term AI as defined in section 2.1. This helped create a shared understanding of the topic for the rest of the interview (Myers and Newman, 2007). In the second part of the interview, we asked for AI projects the interviewees were involved in, including their experience regarding contextual factors and possible organizational challenges and opportunities. We used open-ended questions to generate rich data and ensure an in depth-research approach (Myers and Newman, 2007; Schultze and Avital, 2011). The interviews lasted between 30 and 60 minutes and were either face to face or via video calls. With the experts’ consent, we audio-recorded and transcribed the interviews for further analysis. Example questions included: What are special characteristics of the banking industry regarding the use of AI? Which fields of application for AI are you currently pursuing? Can you think of a project you have recently carried out? Why did you do this project? What opportunities does the use of AI applications create for your company? What were success factors for the implementation of AI-related projects? What challenges did you encounter?

We identified further questions based on early data analysis using theoretical sampling (Charmaz, 2014). Our first interviewees were current or past members of IT management within different banks. As most banks mentioned how their IT struggled with outsourcing and the implementation of AI applications, we also turned to service providers like consultancies and a data center to gain insight on

how they leverage or hinder AI adoption. After we determined that AI applications in retail banks were still at an early stage even though they invested in knowledge and infrastructure, we turned to FinTechs with a close connection to the banking industry. That is, these FinTechs were either collaborating with the banks on AI projects or competing with them in certain areas. Interviews with FinTech founders turned out to be particularly insightful because most of them had a background in the banking industry and therefore provided experiences regarding incumbents and challenges of current business models.

3.2 Data analysis

In coding our interviews, we followed a three-stage coding process in line with recommendations for grounded theory research by Strauss and Corbin (1990). In the initial open coding stage, we focused on early concept discovery. We continued with axial coding, exploring relevant phenomena, relationships, and context. In the last step, we applied selective coding to “construct and fill the storyline around the core phenomenon” (Strauss and Corbin, 1990). The interviews were coded by the same authors who conducted them to also consider the interviewees’ intentions beyond written transcripts. We recorded emerging concepts in memos and organized codes in data trees. Tool-wise, we used the MAXQDA software package to support coding and manage data volume (Saillard, 2011).

In the first cycle (open coding), we started with open coding of 13 interviews and labelled categories and properties from incidents within the data, preferably using the interviewees’ words. We enhanced this procedure by discussing concepts within the research team. Next, the same author continued with a second open coding round for the remaining interviews. We discussed emerging insights and links to align the second round with the theoretical considerations. Based on this, we derived 1149 codes in 23 categories and 10 subcategories. We concluded with core concepts regarding current investments made to benefit from future AI applications and banks’ struggle to cope with contextual factors.

Axial coding was the second coding cycle, in which we systematically developed digital options processes following established literature (i.e., Rolland et al., 2018; Sandberg et al., 2014; Svahn et al., 2015) and laid out the impact of contextual factors following the TOE framework. Also, we excluded categories, subcategories, and codes with no direct link to digital options. This resulted in 888 codes in 17 categories regarding digital options processes and TOE impact. We continuously reflected on the data and our emerging understanding through memoing (Saldaña, 2013). Further, we used digital options literature to triangulate our conceptualization of digital options theory (Flick et al., 2010).

In the third cycle, we used selective coding in line with our background literature to identify core phenomena and discarded phenomena mentioned by only some interviewees. For example, as digital options’ realization was not an emerging theme within our interviews, we focused on the transition of available to actionable options and the generation of options. After identifying and consolidating the digital options concepts, we developed preliminary illustrative indicators that provide a starting point for future research to assess digital options. Table 3 presents examples of coded segments found in several interviews: open codes, both axial codes, and themes emerging from selective coding.

Interview statement	Open Codes	<i>Axial I (italic),</i> Axial II (bold) Codes	Themes emerging from selective coding
“We try to include our colleagues on the business side while prototyping as they are using the application.”	AI project management	DO develop, Organization Actionable Options through communication processes	Organizational factors support the development of digital options.
“The IT landscape often prevents any involvement of intelligent people. Approaches like ‘we could use this’ or ‘let’s find out about it’ are not possible with current systems.”	Legacy IT	<i>DO identify, Technology readiness</i> Hindering of digital option identification through technology readiness	Technological factors significantly impact digital options’ identification process.

“People are not allowed to share data between different departments; Legal/ Compliance prohibited this.”	Compliance	<i>DO generate, Regulatory environment</i> Hindering of digital option generation through regulation	Environmental factors slow down/prevent the generation of digital options.
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Table 3. Coding examples.

4 Findings

Our findings are threefold: First, we find that AI-related digital options in retail banking require a conscious ‘generate’ process to make specific AI options available in the first place. By actively investing in technological readiness and a broad knowledge base, organizations can generate a plethora of available digital options. Second, we find that TOE factors strongly influence the digital options lifecycle. Third, we find that this influence differs along the steps of the options’ lifecycle depending on the type of contextual factors (e.g., technological readiness, know-how, or regulation).

4.1 Generating digital options

Given the nature of AI as a constantly moving frontier (Berente et al., 2021), we find that successfully managing AI-related capability investments requires a conscious ‘generate’ process step. If retail banks cannot source off-the-shelf AI applications from the market, they have to invest in foundational IT capabilities to generate opportunities for later investments in specific AI-related capabilities. Many of our interviewees elaborated on how retail banks actively made baseline investments to create the prerequisites for AI options. Often, data lakes and platform solutions introduced the necessary infrastructure for future AI applications. As interviewee I03 pointed out: “*We are currently creating prerequisites like better data availability and integration architecture. In the long run, this should help us realize AI use cases.*” Also, banks invested in acquiring know-how and created teams solely dedicated to experimenting and learning about AI applications, thus creating organizational capabilities. As interviewee I21 described: “*the basic idea was to establish a team of analysts and developers that would be able to provide solutions to sales.*”

That is, they used the ‘generate’ process to make generic, baseline investments that benefitted multiple options. Such investments are not specific to individual AI applications. Instead, they create basic organizational capabilities such as innovativeness, technical know-how, and interdisciplinarity. Not tying basic investments to specific applications puts organizations in a position where they can explore a broad range of competitive advantages instead of pursuing incremental, case-specific progress. As interviewee I04 described: “*We are building a global, common IT platform that allows us to faster build specific components and then distribute them to each country. These components do not have to run centrally but are developed centrally under one architectural paradigm. [...] We can use this platform for different purposes. And of course, this also applies to the topic of Big Data.*” Figure 1 displays the lifecycle from available to realized digital options, including the ‘generate’ process.



Figure 1. The digital options lifecycle.

4.2 Relevance of TOE factors with regard to digital options

While establishing these basic capabilities, banks often accounted for applicable regulations. These considerations also played an important role in determining if an application was feasible and desirable. Moreover, technological, and organizational factors played an influential role in the identification and development of AI options. Figure 2 visualizes these effects. As mentioned in

section 3.2, we focus on the transition of available to actionable options and the generation of available options as digital options’ realization was not an emerging theme within our interviews. In line with our selective coding, we present the most prominent effects in the following.

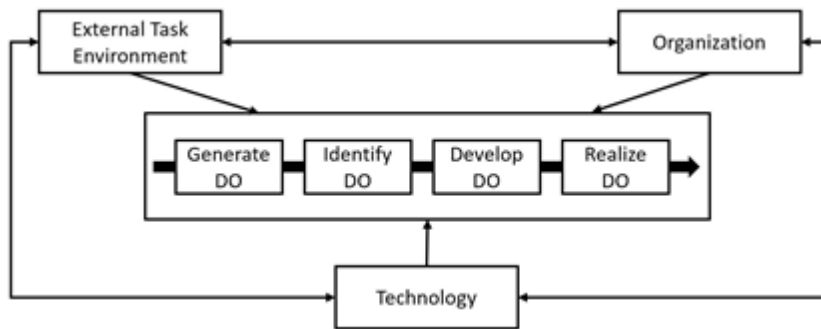


Figure 2. Impact of TOE factors on digital options processes.

During the ‘generate’ process, organizations need to take a long-term perspective and consider internal as well as external factors that may impact the viability of digital options. First, the organization must align internal factors to achieve organizational prerequisites: involvement of top management, the buildup of know-how, and information reach between departments. As interviewee I03 pointed out: *“Building up own know-how takes a long time. We needed to find the right people first, who then had to arrive in the company. Afterward, we had to establish methods and processes and so on.”* Second, organizations must establish technological prerequisites by investing and extending existing infrastructure based on the characteristics of the new technology. Our interviewees described how banks chose different approaches for the generation of AI options. Some adopted a broader perspective and invested in establishing organizational capabilities such as AI project management and data mining know-how. As interviewee I18 described: *“Our idea was that the bank needs a platform especially if we want to build applications hungry for data.”* Others took a narrower perspective and created a data lake to improve service quality needed for a few specific applications. As interviewee I21 described: *“We are creating a data lake with the goal or the vision to someday have all relevant data readily available in this secondary system for analysis.”*

Banks that did not make any investments struggled with data availability and were sometimes even prevented from implementing AI applications. Some interviewees also mentioned how organizational factors such as complex formal structures with steep hierarchies blocked the generation process. Interviewee I01 specifically described how the IT department stood in the way of AI projects: *“They [the management] still don’t have the know-how and have to rely on every statement of the IT department. If IT says, “it’s not possible”, then it’s not possible.”* To circumvent this, other banks decided to introduce largely autonomous development teams to build know-how and experiment with use cases covering various options ranging from current to long-term. Interviewee I02 described: *“We have a dedicated AI team, which has a list of use cases, that they process one after the other. [...] In many cases, the first approaches are not successful. You first have to find the right models. Therefore, we provide the team freedom. There are no strict processes.”*

From an environmental perspective, government regulation strongly influences the generation process in retail banking. Regulation in banking poses a risk because it is typically reactive rather than proactive: When new technologies and their applications are not yet regulated, this will likely change in future. Moreover, existing regulations such as the General Data Protection Regulation (GDPR) can negatively affect future applications. Even when it was not clear if the GDPR would have an effect, mere uncertainty led certain banks to refrain from investments. As interviewee I04 described: *“There are also cases that simply are very difficult, particularly when it comes to combining customer service with some kind of sales activities. I don’t think that this would work right now. We would either have to get the customer’s consent, which is difficult, or refrain from doing it all.”* In other cases, data

privacy regulation limited data availability, prevented experimentation, and led to substantial costs for data anonymization (technology) or legal experts (organization). As interviewee I1 described: *“We invested a lot of time in discussing how to anonymize the data with her [the organization’s lawyer]. Right now, we are allowed to store data for thirty days for evaluation and development. And in these thirty days, we have to anonymize the entire database. Lastly, working students check every single line to assess the data quality and correct it if necessary to improve the training data. We can keep this anonymized data because it can no longer be attributed to any person.”*

The ‘*identify*’ process aims to recognize available digital options. By its nature, it strongly relies on information availability. That is, the identification process depends on existing organizational knowledge as well as evaluations of a technology’s potential impact on business models and processes. To foster this process, organizations can use structures that support information exchange between technological (e.g., IT department) and business experts by, for instance, establishing multidisciplinary teams. In the retail banking context, banks particularly introduced collaborations between data scientists and business departments to identify desirable applications. As interviewee I13 described: *“First of all, there has to be someone on the business side who can properly specify the requirements. In other words, there has to be a data expert on the business side at the bank who can explain to the IT staff what they actually need and correctly specify their requirements.”* In cases where responsibilities were unclear, or support from higher management was lacking, the identification process was disrupted. As interviewee I19 described: *“We hired people to bring data to life. [...] However, they currently report to the head of IT and are tasked almost exclusively with ‘run the bank’ duties.”* A lack of technological readiness also hampered the process as low data availability and high complexity of established systems prevented the exploration of available data. As interviewee I13 emphasized: *“The current IT landscape of banks often prevents accessing the data.”* Environmental factors were less prominent at this stage.

The ‘*develop*’ process strives to “evaluate and bundle new technical and informational features into competitive actions that are both desirable and feasible” (Rolland et al., 2018). This process is heavily influenced by organizational know-how regarding technological characteristics and regulation. In banking, data scientists evaluated the technical feasibility while the compliance department assessed the legal side. Regulation was the main reason banks classified potential applications as non-feasible, sometimes due to insufficient knowledge regarding technology and implementation. Interviewees considered potential applications as desirable yet unfeasible because regulation demands explanation of specific results. Decision-makers expected AI to have a black box problem. As interviewee I02 described: *“You just have to see how it evolves because the regulator will ask transparency regarding the rules that applied in a particular case and that is, of course, difficult to verify.”* Although less mentioned, organizational factors also had an impact. Information reach between compliance, business departments, and data scientists was necessary to determine feasibility and desirability. The compliance department had to talk with business departments and data scientists to understand potential legal issues. As interviewee I21 described: *“Generally, we bring different functions together for evaluation purposes. Among these are people from legal, data protection, and cyber security. These people can give guidance. In the end, data protection, however, always has a veto right. Nevertheless, you can also discuss potential solutions with them.”* Moreover, data scientists needed insight from business departments to design use cases that would add business value. Direct involvement of each organizational unit turned out to be preferable to a mediator, as it also fostered the understanding of AI within departments. As interviewee I13 described, data scientists and their know-how were crucial as they helped business departments to determine the feasibility of their ideas: *“We need both the business and the technical side. The business side needs to understand the business and needs to know what data analytics is all about. Then you need the IT side to implement it and to provide the technology. [...] And then you also need someone who intensively engages with the data and can assess the business side’s ideas with respect to the potentials in the data.”*

4.3 Varying impact along the lifecycle

The three most mentioned factors that had differing impacts on digital options were technological readiness (technology), know-how (organization), and regulation (environment). Our interviews also pointed toward changes in impact of these factors over the digital options lifecycle. Based on comparing code relations, we find that the impact decreased, varied, or remained stable (see Table 4).

Improving technological readiness directly generated new digital options. Our interviewees strongly emphasized this for retail banking. As Interviewee I03 described: *“We are already building the prerequisites throughout our IT to be, for instance, able to access our data more easily and have a better, more structured integration architecture. Of course, all of this will pay off in terms of that we at some point will be able to actually implement AI use cases.”* We find fewer references on the influence of technological readiness on identification and development in our interviews. Therefrom, we draw that the impact can decrease from digital options becoming available to actionable.

General know-how regarding the technology and potentially arising challenges remained equally impactful through the lifecycle and across the organizational hierarchy. That is, banks needed to make sure to build know-how regarding AI and secure a proper know-how transfer throughout the organization to increase awareness for potential application, to support the recognition of available options and make them actionable. Interviewee I02 described that continuous knowledge transfer played an important role in their organization: *“[...] but their task still is to explain the topic to the broader workforce including the arising challenges. [...] They publish the information in our intranet but also organize events and lectures.”*

Environmental factors had less impact during the ‘generate’ phase compared to technological factors. Nevertheless, regulation strongly influenced investment decisions on AI options. Interviewee I05 specified that banks avoid certain investments due to risks: *“Banks are always afraid of regulation and potential missteps.”* Within the identification process, regulation was not the predominant factor. Still, it influenced data availability. As interviewee I13 described: *“He [the specialist] might know about systems containing data that would be interesting for the use case, but he has no access [...] and needs to talk to legal and compliance.”* However, similar to investment decisions in the generation process, regulatory pressure strongly constrained banks’ feasibility and desirability assessments. Interviewee I04 described how GDPR influenced potential projects: *“We are very, very precise on the legal side in Germany and would rather take a step less than one too many.”*

	Generation	Identification	Development
Technology Readiness (T)	Technological requirements for the availability of digital options. (36).	Open systems enabling an analysis of potential areas of application. (5).	Potential costs arising with new applications (e.g., building an infrastructure) possibly rendering options not feasible. (4).
	Decreasing influence		
Know-How (O)	Awareness within the company (especially management) regarding new technologies. (11).	Knowledge in business departments is fundamental for identifying potential options. (10).	Knowledge regarding regulation (feasibility) and technology (desirability/ feasibility). (6).
	Stable influence		
Regulation (E)	Costs/risks related to applications not yet regulated. (16).	Influence on senior management to refrain from using internal capacities. (7).	Influence on feasibility assessment (AI ‘black box’ problem). (31).
	Fluctuating influence		

Table 4. TOE factors’ impact on digital options process; number of cross-coded segments in ().

5 Discussion

In our study, we explore how retail banks can successfully manage their investments in AI-related IT capabilities. These capability investments generate digital options, which eventually enable banks to pursue AI applications. However, organizations do neither generate nor realize digital options in isolation. We demonstrate that TOE factors not only influence the individual processes but have different impact patterns throughout the entire digital options lifecycle.

While Sambamurthy et al. (2003) already mention the role of “IT as a digital options generator”, recent literature often focuses on available options. Accordingly, research has introduced the process steps ‘identify’, ‘develop’, and ‘realize’ (Rolland et al., 2018; Sandberg et al., 2014) but refrained from further elaborating on digital options generation. Based on existing IT and organizational capabilities, the assessment process in current literature starts with a set of potentially available options rather than a first investment (Rolland et al., 2018). Although this process supports IT investments capable of enhancing current business, it falls short when it comes to new technologies, such as AI, that have the potential to disrupt existing processes and business models. Based on our interviews, we emphasize the importance of analyzing the step of initial investments to generate digital options. During generation, managers can actively invest in preparing their organization and IT capabilities to benefit from applying AI in the future. Moreover, our research builds a bridge between digital options thinking and real options analysis (ROA), which is concerned with an ex-ante valuation of IT investment projects (Müller et al., 2016; Ullrich, 2013). Thus, it can function as a starting point for prescriptive research on valuating AI initiatives. Based on relaxed assumptions, ROA can provide managers with a valuable tool to assess option generating investments in the context of AI (Müller et al., 2016). Complementary to the process described in the literature, we argue that the initial investment does not have to support current business performance. Although it might contribute to it, it mainly enlarges the pool of digital options that may be realized in future. Digital options thinking, thus, also provides value to AI research and practices beyond valuation aspects (Fichman et al., 2005).

Digital options theory provides a broad perspective by abstracting from specific use cases and focusing on capability investments that allow for a broad range of applications. This broad perspective can be particularly helpful for the banking industry as it is such an interdisciplinary field that holds the potential to combine various AI technologies at once (Bahrammirzaee, 2010). For instance, AI can increase process efficiencies (Fethi and Pasiouras, 2010), enhance financial market predictions (Aydin and Cavdar, 2015; Bahrammirzaee, 2010), or cash demand forecasting in ATMs (Bhandari and Gill, 2016). AI can also help addressing regulatory aspects such as anti-money laundering and anti-fraud (Chen et al., 2018; Kute et al., 2021). Our findings illustrate how banks invested in organizational capabilities to benefit from AI and potential use cases: they introduced multidisciplinary teams to expand technical knowledge or support use case development. Additionally, these banks enhanced data availability via different means: some banks went as far as investing in data lakes which did not benefit current processes but instead offered the possibility to experiment with data, therefore contributing to the overall AI readiness of the bank (Holmström, 2021; Jöhnk et al., 2021). It remains unclear whether this approach provides a competitive edge in the future, as the banks’ AI applications were still at an early stage. That is, banks need to realize these options in the future based on an assessment of their feasibility and desirability.

The assessment of this feasibility and desirability depends on different factors. Digital options theory commonly takes a process perspective focusing on internal information, process requirements, and generative capabilities (Rolland et al., 2018; Sandberg et al., 2014; Svahn et al., 2015.). However, discussing how processes shape the requirements for digital options is too narrow. External factors also pose a risk if they are not considered within the digital options lifecycle. Although Svahn et al. (2015) mention context factors such as industry trends, product settings, and innovation vision as crucial, they mainly focus on building organizational capabilities to cope with the context and, as such, only identify relevant management processes already in place. Based on our findings, we argue that the TOE framework complements existing context-awareness in digital options theory. TOE factors affect the entire digital options lifecycle (see Figure 2). This is consistent with recent AI research that,

for instance, finds organizational factors such as the presence of a CIO or boards of directors with a higher educational diversity as well as experiences in R&D and AI to positively influence an organization's AI orientation (Li et al., 2021). Moreover, TOE factors could significantly impact the decision to realize specific AI applications. That is, managers should understand how both endogenous and exogenous factors affect or even hinder decision making during the realization process. If changes occur during the process, managers can react and adapt their strategies and discard digital options, similar to closing existing option positions on the financial market (Sandberg et al., 2014). Additionally, managers should be aware that the impact of contextual factors can vary depending on the process step and its objective (see Table 4). Being aware of the varying impact of TOE factors along the entire lifecycle puts organizations in a position to assess their projects' feasibility as it helps to balance resources and account for various implementation conditions, thus, creating competitive advantage (Sandberg et al., 2014). Moreover, it adds to an organization's agility to react to opportunities that might be unknown at the time of the initial IT investment and enable them to "seize [...] competitive market opportunities by assembling requisite assets, knowledge, and relationships with speed and surprise" (Sambamurthy et al., 2003).

Drawing on both digital options theory and the TOE framework, our research contributes to the increasing body of knowledge on AI adoption. While some studies already incorporate the TOE factors in assessing AI readiness (e.g., Alsheibani et al., 2018; Jöhnk et al., 2021), our study adds a structured approach to consciously balance resources and AI-related capability investments. This approach is particularly helpful in complex environments characterized by many endogenous and exogenous dependencies (organizational and technical), such as retail banking. In this way, our study also complements recent research on the interplay between incumbents' resources and digital opportunities (Oberländer et al., 2021) and points a way for banks to move from their existing resources to realizing the potential of AI.

6 Limitations and further research

While providing insight into how retail banks invest in AI-related IT capabilities, our research has certain limitations. For instance, we only interviewed a limited number of bank employees. While our interviewees from IT consultancies, FinTechs and service providers helped us get a diverse perspective on the problem at hand, their knowledge of banks' internal affairs was limited. Furthermore, the interviewed organizations were primarily based in German-speaking countries, particularly the DACH region, restricting the research's external validity (e.g., regulation but also the degree of digitalization differ depending on the geographical setting). Consequently, future research could benefit from further interviews in banks in different economies. Besides limited interviewee choice and availability, the current state of AI adoption in retail banking also restricts our research. Since most banks had not achieved a set of actionable AI options yet when we interviewed them, practical implications of our study regarding the realization of digital options are limited.

Our research's limitations also indicate possible avenues for further research regarding TOE factors and digital options theory. First, with technological readiness being the most prominent TOE factor emerging from our coding, we see opportunity to more deeply analyze its effects in the context of emerging technology adoption, offering additional practical and theoretical implications. Also, scholars could explore the impact of different contextual factors on the generation step of digital options. Second, digital options theory remains a promising research field. While previous research focused on available options, we introduce and emphasize a step to consciously generate digital options. Although our work uncovered differences regarding the digital options process between existing and emerging technology, scholars could derive further dissimilarities to potentially complement these findings. Moreover, future research could also investigate the valuation aspects of digital option in the context of AI in more detail.

Overall, our study demonstrates that digital options thinking with consideration of contextual factors can help better understand the adoption of AI in retail banking. We hope that our research will fuel a discussion on and further investigations of digital options in the context of AI.

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