From Hype to Habit: What are the drivers behind AI adoption in the consumer goods industry?

A qualitative study on the factors enabling digital transformation within fast-moving consumer goods companies in emerging markets

BE151: Degree Project in Management

AAYUSH GUPTA
MAX LJUNGGREN

Bachelor Thesis

Stockholm School of Economics

2025

Abstract:

Artificial Intelligence (AI) is a disruptive technology and a digital transformation that can have fundamental impacts on business and has become a source of value for various industries. This holds true for the Fast Moving Consumer Goods (FMCG) industry which is the subject of this thesis to investigate the factors influencing the decision to adopt AI technologies within the FMCG industry and within emerging markets and developing economies (EMDEs). Understanding the enablers and barriers specific to this context is vital for both theory and practice as these technologies are becoming an integral part of the digital business model and represent an opportunity to gain and maintain global competitiveness and bridge the gap between developing and developed economies through efficiency gains and cost savings.
A qualitative, multiple case study methodology was employed, involving semi-structured interviews with key decision-makers with knowledge of AI and its adoption across three FMCG firms with operations in India and Southeast Asia. Data collection and analysis was guided through the TOE framework and thematic analysis. Findings indicate that factors such as perceived compatibility, data readiness, and IT infrastructure are critical technological enablers to the decision to adopt AI within FMCG, while barriers include quality of data, lack of technical expertise, and system integration issues. Organizational factors such as top management support, internal champions, and upskilling initiatives emerged as essential for successful adoption. Environmental influences, including regulatory constraints, local infrastructure, and competitive pressure, were found to vary in impact depending on market position and geography.

***Keywords**:* Artificial Intelligence, AI adoption decision, Fast-moving consumer goods, Emerging markets and developing economies, TOE framework

***Title**:* From Hype to Habit: What are the drivers behind AI adoption in the consumer goods industry?

***Authors**:* Aayush Gupta (25623), Max Ljunggren (25587)

***Supervisor**:* Ebba Henrekson, Researcher, Center for Educational Leadership and Excellence

***Examiner**:* Laurence Romani, Associate Professor, Department of Management and Organization

Bachelor Thesis
Bachelor Program in Business & Economics
Stockholm School of Economics

Acknowledgments

We would like to start by extending our thanks to the participants who took part in our study, your willingness to cooperate and the many insights you have all provided to enrich our analysis and understanding of the underlying contexts surrounding our research topic. We would like to thank our supervisor, Ebba Henrekson, for all the guidance and feedback you provided us with during the process of writing our thesis, and for challenging us to think more critically during our writing process. We would also like to thank our supervisory group, your feedback and advice given during the process was crucial in refining our research question and research aim, as well as the overall formatting and flow of the thesis. We also thank and acknowledge our examiner, Laurence Romani, for your presence before and during the writing process, assistance along the way, and the informational sessions organized for all thesis takers. Finally, we want to extend our gratitude to our friends and family, for the many conversations bouncing ideas back-and-forth and the emotional support provided during this time.

Max & Aayush

Table of Contents

Definition Table:

Term	Definition
Artificial Intelligence (AI)	Systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving,
Narrow (Weak) AI	AI which possess specialized abilities, which surpass that of humans. These systems are focused on one particular area and excel at that task but lack the general cognitive abilities of human intelligence. (Ex: AI-Assisted Robotic Surgery, Image Recognition, Predictive Maintenance)
Generative AI (GenAI)	AI that possesses similar, if not the same level of ability as humans with comparable efficiency. This form of AI relies on machine learning to simulate human learning and decision-making. (Ex: ChatGPT, Inventory Optimization, NLP Tools)
Strong AI	AI that exhibits superior abilities towards that of humans, over a wide variety of areas. This form of AI aims to imitate human intelligence and possesses the capability to understand, learn and apply knowledge over a wide variety of tasks. Though only a theoretical concept, the idea and current ongoing research can have significant implications and disruptions on future business processes and society in general.
Digital Transformations	The integration of new technologies into all areas of a company.
Emerging Markets and Developing Economies (EMDEs)	A term coined by the International Monetary Fund (IMF) in the World Economic Outlook (WEO) to classify countries based on aggregated economic data. These are countries that do not meet the criteria set by the IMF to be classified as advanced economies and are characterized in recent times as accounting for 85 percent of the growth in global consumption and close to 80 percent of global economic growth. ***Note: These terms are used interchangeably throughout the thesis as a reference to countries that meet these criteria***

1. Introduction

1.1 Background

Fast Moving Consumer Goods (FMCG) businesses in developing economies are beginning to recognize the potential of adopting AI technologies within their business processes as an opportunity to achieve and maintain global competitiveness through an optimization of their operations and overall productivity gains (Ikpe, 2024). Key competitive factors in the fast-moving-consumer-goods (FMCG) industry include efficiency, quality, and consumer satisfaction (Olutimehin et al., 2024). Particularly, the most useful implications of adopting AI into FMCGs include demand forecasting, personalized marketing and inventory management, supply chain optimization and quality control.

The FMCG industry is characterized mainly by products which are perishable and in high demand and often require timely delivery as these goods are often consumed on a daily basis. In such an industry, there is intense competition both locally and globally, and the time and cost of delivery are important factors when considering a supplier. This places importance in supply chain management for operational efficiency and interconnectedness from suppliers to the end user (Nozari et al., 2021). Adopting AI technologies as a supply chain management strategy can have significant efficiency and productivity gains in the delivery and distribution systems.

AI is moving at a fast pace and is a transformative technology which plays a role in several integral parts of many organizations' core business model and is simply defined by Russel and Norvig (2016) as systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving. The implications of AI technologies are a widely researched and discussed topic within the world of business and management and presents an opportunity for business to adapt this technology to specific roles and tasks which are currently being performed by humans. This has implications on the FMCG Industry of which its processes are heavily imbued with the use of data for customer insights and decision-making in which several of its data-intense core business processes and tasks can be automated with the adoption of AI technologies (Olufemi-Phillips, 2024).

The impact of AI technologies can be significant, especially when considering its adoption in businesses in developing economies. Developed economies have been faster to reach widespread levels of adoption for such technologies, however in countries like India, China, Brazil, Mexico, and South Africa, there has been an increase in AI adoption among businesses in recent years. (Ikpe, 2024) By leveraging AI technologies, businesses can automate repetitive tasks, analyze large datasets to gain valuable insights and personalize marketing strategies as well as optimize various business processes (Trillo et al., 2023). Ultimately, this can lead to cost-savings and efficiency gains substantial enough to gain a competitive edge and share in the global market (Bengio et al., 2017). Additionally, these predictive capabilities of AI can be significant drivers of growth with AIs' rapid evolution.

1.2 Research Gap

There are ongoing and recent academic studies on the organizational, environmental and cultural factors which determine successful implementation of AI and digital transformation into organizations in general (Ångström, 2023; Lee et al., 2023), as well as factors across professional service (Yang, 2024), SME (Ikpe, 2024) and manufacturing (Sharma, 2022) companies within emerging markets and developing economies (EMDEs). However, there is less empirical evidence for the factors which enable the adoption of such technologies into its business processes and operations specifically within the FMCG industry and for emerging markets.

While AI implementation is becoming increasingly important in this new business landscape, especially within FMCG companies, there is limited research on how different factors interplay and influence the decision to adopt, especially when delimited to emerging markets.

1.3 Aim and Research Question

Research Aim

In this study we are aiming to identify the key technological, organizational, and environmental (TOE) factors influencing the decision to adopt AI in FMCG companies within emerging markets and developing economies, with the aim being to explore and discuss said factors. Specifically, this study is seeking to understand how these factors influence the decision to adopt AI technologies, as well as the challenges and opportunities these organizations have faced, which can provide insights for navigating digital transformations.

Research Question:

How are the key technological, organizational, and environmental factors influencing the decision to adopt artificial intelligence in fast-moving consumer goods (FMCG) companies within emerging markets?

This study intends to address the (research) gap through a qualitative, multiple case-study, of FMCG companies in emerging markets with the aid of the TOE (technological, organizational, environmental) framework and interviews with key decision-makers from FMCG business in emerging markets to gain their insights and perspectives on and current uses of AI as well as factors influence their adoption or lack thereof. This is especially relevant when considering the rate at which AI is developing and being implemented into business processes.

1.4 Delimitation

The study involved several delimitations, including; the geographical scope, industry type, and company size. The geographical scope is focused on emerging markets and developing economics (EMDEs) in the Asia Pacific (APAC) region. Developed economies are purposefully excluded due to stark differences in IT infrastructure, regulatory environment, business environments, and perceptions regarding AI. The industry type is fast-moving consumer goods (FMCG). As FMCG firms are heavily manufacturing oriented with a high level of emphasis on supply chain management, AI adoption can be deployed to optimize these processes. Finally, the study only includes mid-to-large size companies, this is because of the assumption that smaller firms have fundamentally different technological, financial, and organizational challenges preventing them from adopting these technologies.

2. Literature Review

2.1 Digital Transformations and AI

Digital Transformations

Digital Transformations can be broadly defined as the integration of new technologies into all areas of a company. (Foradellas, 2021) These transformations often disrupt and require the transformation of traditional business models. Artificial Intelligence represents one of the most relevant disruptive technologies in recent time and has significant implications on business and people with its potential impact highly related to the adoption of these technologies. These technologies have the potential to make use of data to generate new relevant information, improve operational efficiency, boost sales and improve consumer outcomes (*Ibid*).

The rise of digital technologies has become an important driver for change in multiple industries (Rossman, 2018), with digital transformation and artificial intelligence changing business models and improving communication between people, in turn facilitating new business structures (Foradellas, 2021). These technologies have potential impact on all levels of the firm including internal processes, business model frameworks, and customer experiences (Sugathon et al., 2018). Therefore, businesses need to develop capabilities, including technological and organizational ones, in order to manage the transformation process successfully in order to realize its potential impact. An example of the digital environment created as well as the impact of these technologies on a business' core business model can be shown as below:

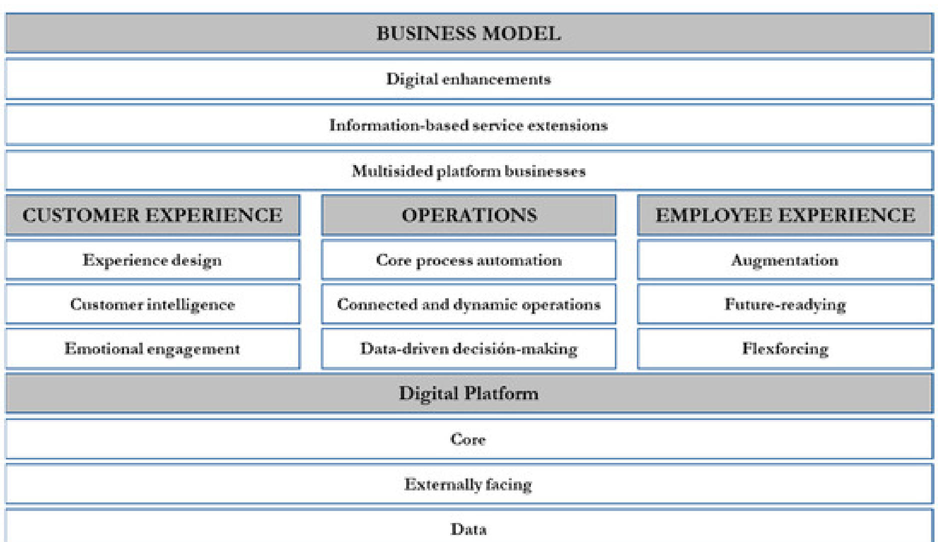


Fig 1. Digital Business Model

2.2 AI In FMCG Company Processes

FMCG companies are constantly striving to meet consumer demands whilst maintaining operational efficiency (Benfratello & Shiqian, 2021). Characterized by high levels of competition, changing consumer demands and tight margins, strategic operations management (SOM) plays a vital role in determining the effectiveness of internal business processes for these companies (Olutimehin et al., 2024). As such, it is relevant for FMCG companies, especially those within EMDEs, to enhance their operations through the best practices and remain adaptable to innovations or trends within the industry and internal processes to achieve a competitive advantage (*Ibid*). One such ongoing trend in SOM is that of a finding through a global study with executives from varying industries and countries where 85% of surveyed executives are projected to invest heavily in AI technologies within the next three years (Lee, 2023). Heavy global investment shows that there is significant belief in these technologies to reshape the business landscape and solve organizational challenges, with heavy investments into artificial intelligence and its implementation following. This trend can also be viewed in the Global AI Survey McKinsey Report (Nov 2019) where adoption of AI is described as increasing and there is a significant increase in revenue and reduction in costs, especially where AI has been adopted to several business processes.For a more in detail breakdown of AI uses cases in FMCG (see Appendix A)

2.3 Previous Research on AI Adoption

Through findings and previous research on AI adoption in various environments and industries, three factors emerge as common, clear business benefit, usable data, and support from top management. However, the relative weight of these factors is different across industries. In an Indian study on AI within agriculture, supply chains are implementing AI in a bid to increase efficiency and improve product tracking, but are reporting product stalls due to issues surrounding data quality (Jain, 2021). Similarly, in Europe, the agricultural sector has also identified data quality as a pain point, while also adding that the use of older software makes AI implementation more challenging. Another study found that once data pipelines were fixed, demand-forecasting accuracy became the top driver and regulations became less important to the decision to adopt (Mubarok, 2023). Within professional services a different conclusion was reached, a study done on Swedish law and consultancy firms found that client confidentiality and the veto power of the legal team on these grounds is a bigger influencing factor than an internal advocate (change agent). Finally, a worldwide survey of 2,300 companies, where these companies have the IT infrastructure and technical capabilities to implement AI (Ångström, 2023) found that the biggest hurdle was employee perceptions. Projects move only when it is a top-down initiative, with adequate upskilling, and the positioning of AI experts within teams.

3. Theoretical Positioning

3.1 Technology–Organization–Environment (TOE) Framework

The TOE framework, proposed in the book: The Process of Technological Innovation (Tornatzky et. al. 1990), is a theoretical framework that provides a model for understanding technology adoption in organizations. The TOE framework suggests that the adoption of technological innovations are influenced by technological, organizational, and environmental factors (Oliveira & Martin, 2011). All these factors are considered to be interrelated, and play a crucial role in understanding the adoption and implementation of AI within FMCG organizations. The TOE framework is an organizational-level theory, and has the ability to adapt to the context.

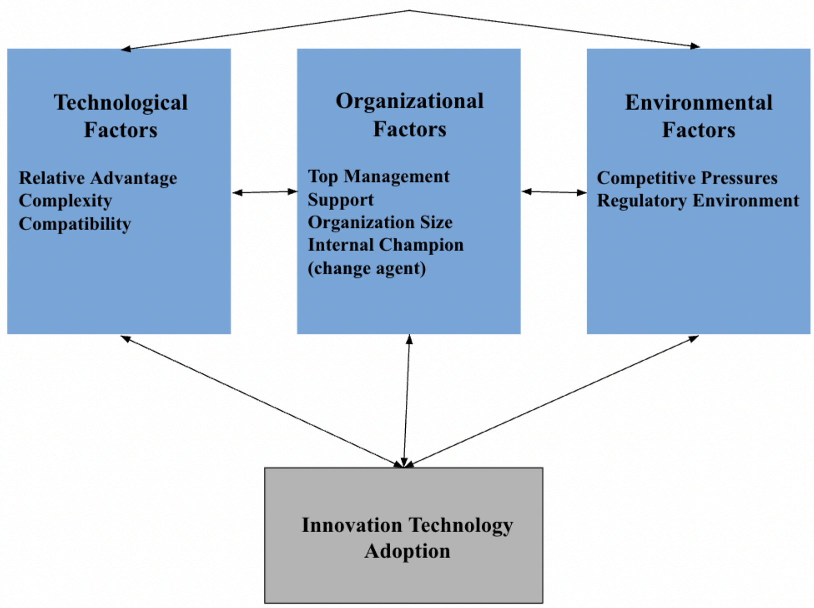


fig.2: The TOE framework (Gupta & Ljunggren, 2025)

Technological Factors

Diffusion of Innovation (DOI) theory (Roger, 2003) is also an organizational level theory, and is widely applied in the study of technology adoption. Scholars have used the TOE framework alongside DOI theory for uses such as, adding innovation attributes (relative advantage, complexity, and compatibility) from DOI (Chong et al., 2009; Wang et al., 2010). Thong (1999) added CEO characteristics from DOI into TOE. Rogers (2003) identified five technological attributes that are necessary for an adoption decision: relative advantage, compatibility, complexity, trialability, and observability. This study will only focus on the first three as the latter two are found to be less influential (Yang et al., 2015; Grover, 1993). This was also confirmed by Tornatzky and Klein (1982), which found only relative advantage, complexity, and compatibility often play a role in innovation adoption.

Research shows that the increased efficiency, accuracy, and reduced operational costs (Ramdani et al., 2009) are key drivers in AI adoption. Additionally, AI ability to integrate within existing technologies used by the organization (ERP systems), play a significant role in the perceived advantages of AI over traditional methods. Perceived complexity, as noted by Rogers (2003) is negatively related to the rate of adoption. Firms are more likely to adopt AI into business processes when it is perceived as compatible with the existing IT infrastructure, causing minimal disruptions, and providing clear tangible benefits (Yang et al., 2015; Wang et al., 2010).

Organizational Factors

The organizational factors refer to the internal factors that may impact the firm's ability and willingness to adopt and implement technological innovations. As seen in fig.2, key factors include management support (leadership), size of the organization, and having an internal champion. Support from management is critical in driving adoption of new technologies (Hsu et al., 2019) such as AI, as they are responsible for allocating resources and capacity, as well as fostering an innovative culture (Rodriguez et al., 2008), without which implementation cannot happen. Equally critical, the size and structure of the organization can determine whether the adoption and implementation is successful (Aboelmaged, 2014). Larger organizations have more resources and capacity, and thus are better equipped to adopt, implement, and then scale new technologies (*Ibid*).

Additionally, the third key factor is having an internal champion. An internal champion is the employee who actively supports the change, advocates for it, and has the ability to communicate their vision in a compelling way. Howell and Higgins (1990) concluded that the internal champions enthusiasm for the proposed change, can create the commitment of said change in others.

Environmental Factors

The environmental factors refer to the external (business) environment and how it may influence the adoption of technological innovation. As seen in fig.2, the key factors include competitive pressure and the regulatory environment. As FMCGs are a fast moving industry, and high levels of competition within an industry drives the need for innovation, leading to the adoption and implementation of many new technologies (Zhu et al., 2003). Additionally, regulatory environments play a significant role in AI adoption. The strictness of data privacy laws and ethical usage guidelines can either work to enable or hinder adoption and implementation. As this study is exploring the role of certain factors in enabling AI in FMCGs in emerging markets, understanding the regulatory environment and how it works to either enable or hinder is crucial.

3.2 Criticism of TOE Framework

The TOE framework is widely used within academic research regarding technological innovation adoption, as such it can provide valuable insights into the adoption process. However, the framework's ability to adapt to contexts means that any factors identified may vary across different contexts, and as such the model is limited in its ability to generalize findings across industries (Gangwar and Raoot, 2013). Furthermore, the framework has an overfocus on the initial adoption phase and organizational readiness while neglecting post-adoption phase, scaling, and long term integration This limits the model's ability to explain how the technology should be continuously managed post-implementation. Dedrick and West (2003) criticized the model for being a taxonomy rather than an applicable integrated framework, however they noted it is useful in distinguishing between different contexts that may influence organizational decisions.

3.3 Application of Theory

The Technology-Organization-Environment (TOE) framework is the theoretical lens which will guide our data collection, analysis, and discussion. The framework helps in understanding how the three influencing factors of TOE (technological, organizational, environmental) are interconnected, and their influence on

AI adoption in FMCG companies in emerging markets. The aim of this thesis is to identify the key technological, organizational, and environmental (TOE) factors influencing the decision to adopt AI in FMCG companies within emerging markets and developing economies, with the aim being to explore and discuss said factors, with data being collected through interviews with key decision makers and management, to uncover influencing factors.

In this study the TOE framework will guide a thematic analysis of interview data. Each of the three influence factors provides a lens through which recurring sentiments, perception and/or themes can be identified. The analysis will mainly focus on three areas. Firstly, using TOE to identify how different factors influence the decision to adopt and implement AI solutions. Secondly, gain a better understanding of how these factors influence each other, and how they jointly shaped the decision to implement in FMCGs.

4. Methodology

4.1 Research Philosophy and Approach

4.1.1 Research Paradigm and Ontological Stance

In this study we are aiming to identify the key technological, organizational, and environmental (TOE) factors influencing the decision to adopt AI in FMCG companies within emerging markets, with the aim being to explore and discuss said factors and analyze their interconnectedness. In this regard, the study observes three FMCG firms that have operations in emerging markets. Although the three-case format is unable to yield statistical generalisation, cross-case similarities can be analytically generalised (Yin, 2018, p.40) and fitted to the TOE framework. As such this study adopts a soft-positivist epistemological stance. The organizations being analysed are assumed to have adopted AI-solutions independently of this study, therefore this study adopts an objectivist ontological stance, wherein the AI adoption decision is real and concrete, and it can be studied and compared across firms, regardless of the different contexts. The adoption decisions are enacted by individuals at the firms via their external environment influencing their sense making. In order to capture these insights, the study will have an interpretivist undertone. During the open coding stage, interviewees' words are preserved as in-vivo codes before being mapped onto the TOE categories. This approach allows for identifying patterns while also considering the subjective meaning.

4.1.2 Reasoning Logic

In this study we will be employing an abductive approach, combining both inductive and deductive reasoning. Inductive reasoning is based on experiences, observations, and facts to evaluate situations and make assumptions, while deductive reasoning is based on using logical assumptions, which are accepted as facts, to come to a new logical conclusion. Inductive reasoning is used during open coding, where interview transcripts are coded into in-vivo labels without mapping. Afterwards, deductive reasoning is used to focus code labels, merging the in-vivo codes into parent and child codes which are aligned with the TOE framework (see Appendix B). If there are codes which are discrepant with the TOE framework, this prompts a revision of the theoretical positioning and codebook. Due to the nature of abductive reasoning, there is a wider range of flexibility in response to any new insights, allowing the TOE frameworks' application to evolve in the case that there are new insights.

4.2 Research Design

This study employs a qualitative, multiple-case design to identify key factors influencing the decision to adopt AI across three FMCG firms. Having a single case would delve further into internal dynamics and their effect on AI adoptions, however it would not allow for any cross firm analysis. Three varied firms provide enough contrast to test for analytic generalisation without claiming that the results are representative of statistical generalizations (Yin, 2018).

4.2.1 Case Selection Criteria

In deciding the cases three criteria were applied, industry alignment, regional relevance, and AI-maturity. Industry alignment was to ensure all cases were FMCG firms with a varied product portfolio. This ensures that supply chain pain points and marketing pressures are broadly comparable. Regional relevance was to ensure that all firms had headquarters or significant operations within APAC EMDEs. Finally, AI maturity was to ensure all firms have already made the decision to adopt AI, with each firm varying on the progress towards the roll out.

4.2.2 Unit of Analysis & Replication Testing

The unit of analysis is organizational-level AI adoption decision. Each case acts as a mini-experiment that can then be compared with the others (*Ibid*). All three firms have large scale operations in India, as such it is expected that core technological and organizational issues repeat across them. This is the literal replication test (*Ibid*), if the same pattern shows up for all three, we can assume it is a fact. Company 2 and 3 also have large scale operations in South-East Asia, while company 1 does not (see 4.2.3 Company Profiles). As such factors related to the environment should matter more to company 2 and 3. The theoretical replication (*Ibid*) test, would test to see if external pressures affect 2 and 3 but not 1, if true it would support TOE frameworks claims that the environment helps to shape adoption.

4.2.3 Company Profiles

Company 1, is an Indian liquor and fertilizer manufacturer that uses AI in several aspects of their business processes such as, machine-learning forecasts demand, picking truck routes, and scheduling predictive maintenance for plants. Additionally, a pilot visual-recognition system to track worker and truck movements on premise.

Company 2, a global confectionery and food products manufacturer, which has operations in the Asia-Pacific market. Uses machine learning algorithms to optimize their inventory and capacity planning as well as for supply chain optimization. Additionally, GenAI is used in recipe optimization and for content generation with its main applications being marketing and branding purposes.

Company 3, a global distributor of hygiene and health related goods which has operations in the Asia-Pacific market and in e-commerce, uses AI for, vision analytics at production conveyor belts for ensuring correct label and patch numbers in order to automate their production processes. And demand sensing and sales force automation systems.

4.3 Data Collection

4.3.1 Sampling

The selection of interviewees was purposeful, wherein we specifically targeted either employees who work within AI adoption and implementation/Data Analysis or employees who held senior enough management roles that they could provide a good understanding of the impacts AI adoption has had on their overall business. All the people we spoke with were either directly involved with the parties leading the AI change, or held enough seniority in the organization that they had a good understanding of AI strategy and the organization's thoughts moving forward. There are 9 interviews collected across 3 different companies (see tab.1).

Tab.1: Table showing summary of interviewees

Company	Alias	Role	Date(dd/mm/yy)
Company 1	R1	CIO	08-04-25
Company 1	R2	Assistant General Manager	04-04-25
Company 2	R3	Data Science, AI & Analytics Leader	03-04-25
Company 2	R4	Business Manager - Emerging Markets	02-05-25
Company 2	R5	Market Director	08-05-25
Company 2	R6	Responsible for Supply chain and operations for certain geographies	09-05-25
Company 3	R7	General Manager, Malaysia & Singapore	12-04-25
Company 3	R8	Global IT Lead (Healthcare and Food - Infant Child Nutrition)	02-04-25
Company 3	R9	External Consultant	22-04-25

Note: Apart from R2 and R9, all other respondents agreed to being recorded, therefore insights were collected but not direct quotes.

4.3.2 Interview-guide design and protocol

The interview guide (see Appendix E) was designed with the aim of the thesis, research question, as well as the theoretical positioning in mind. Each participant received the interview guide upon confirmation of their participation, usually 2-3 days prior to the meeting. This was done so that participants understand the type of knowledge we are looking for and can better prepare their answers.

The interview format is semi-structured, giving the respondents flexibility on the topic of exploration, while also ensuring all key topics are covered. Interviews were conducted online via Microsoft Teams, and recorded with the participants consent. Furthermore, Microsoft Teams was used to transcribe meetings. Some participants chose to opt out of the recordings, in which case notes were taken by hand as the meeting progressed. The meeting times also varied from 40 minutes to 2 hours. This variance can be linked to the availability of the participant, their knowledge of the subject, as well as their willingness to engage with tangentially related topics.

4.3.4 Consideration of Alternative Methods of Data Collection

Alternative methods such as surveys or observations were considered, however it was ultimately decided to use an interview based approach. This was because the nature of the research question required in-depth insights into areas such as decision-making, organizational factors, business environment factors, ect.. As such interviewees seemed to be the most suitable way to collect the required data.

4.4 Data Analysis

Transcripts created through Microsoft Teams were verified afterwards using meeting recordings. Transcripts were then imported into NVivo 14, which aided with the analysis. The coding process involved using NVivo 14s AI capabilities to identify patterns in the data, and produced 340 in-vivo labels from the interviewees own words. These labels were then merged into 24 child codes corresponding to 5 parent codes (see appendix B). Throughout the coding process if data was found that was contradictory or belonging in more than one child code, the theoretical positioning and codebook were revised. The 5 parent codes were motive for adoption, technological factors, organizational factors, environmental factors, and future trends/outlook.

4.5 Ethics and Quality of Research

4.5.1 Trustworthiness

Using Lincoln and Guba (1985) criteria for trustworthiness: credibility, transferability, dependability, confirmability. Credibility is supported through our coding process, which involves finding in-vivo labels and then classifying them into our codes, this process was done jointly. Transferability is supported by section 4.3.2 showing details about the company, their use of AI, and the roles of the participants, allowing the reader to decide if the result fits their setting. Dependability is supported by the authors following the same process, as documented here, for all results. Confirmability is supported by the authors having dialogue immediately after the meetings and critical reflection to ensure personal bias is as minimized as possible.

4.5.2 Ethical Considerations

All participants are clearly informed of the purpose of the study, the extent of their participation, as well as the participants right to privacy, under GDPR. All participants have the right to withdraw from the study at any time for any reason, in which case all personal data that may have been collected will be promptly destroyed. Further, to maintain confidentiality all identifiable data will be anonymised, including company name, employee name, gender, age, ect.. The data presented in the study will be aggregated, therein ensuring further anonymity. Participants gave consent either through verbal confirmation or by signing the GDPR consent form provided by the Stockholm School of Economics.

4.6 Use of AI

AI was used throughout the process of researching, drafting, and finalizing the submission of this thesis. ChatGPT was used to aid with the outline of the thesis, as well as certain wordings and formatting choices. Other forms of GenAI were also used for problem solving and other queries related to the writing of the thesis, however all text is the author's own work and not generated by AI. NVivo 15 was a software used for thematic analysis, this software has an AI-driven feature that allowed us to collect in-vivo codes from interview transcripts. Finally, Elicit was used for research alongside ChatGPT o3 (a deep thinking model with internet connectivity)

4.7 Methodological Limitation

The method used in this study has 3 main limitations. Firstly, the three cases represent a sample size that is too small and with them all operating in a similar geography is too local, to claim that these findings can be applied to the enter industry. Secondly, all interviewees were either senior level or low level executives, as such the perceptions and voices of mid level and lower level employees was not considered, which may provide more insights on the decision to adopt AI. Finally, all interviews were conducted online, with some interviewees keeping cameras off. This means that non-verbal communication was not observable and could have led to further insights being developed.

5. Empirical Data

Specific applications of AI for *Company 1* (distillery in India), *Company 2* (multinational manufacturer of food products and confectionaries), *Company 3 (*producer of hygiene and health products), all of which operate and produce in emerging markets, and the influencing factors behind the decision to adopt AI technologies, as analysed through recurring themes in the interviews as well as other important considerations will be listed below.

5.1 Motive for AI Adoption

5.1.1 Increased Efficiency and Cost Savings

A recurring theme throughout the interviews was the importance of formulating a business case for adopting AI technologies. In an industry where margins are thin and there is an increased importance on efficiency and cost-saving, these initiatives should be based on value creation and solving internal business problems. One respondent (R3) describes: "Finance … That's the bottom line of any FMCG" and that "this is all about optimizing pricing." Additionally, they noted that they had several requirements that through their current business processes "cannot be done by humans at scale" and that a use case for "leverag[ing] generative AI to solve this problem" came as a result. It is important to consider whilst the respondent mentioned the decision to adopt AI as a "top driven decision" and AI as a "strategic priority" that when considering solutions to tackle these efficiencies they were made on the basis of "going to the business, defining the problem … then highlighting a solution." Rather than the focus being solely on AI technologies, although often now stated as a strategic objective, the higher management reiterated, in regards to the decision to adopt AI solutions, the importance of a solution that would make for the best business case and provide the most value, with the resulting choice often being an AI solution. The value of AI for FMCG business comes in several different ways, with one respondent (R6) noting "tak[ing] the right call at the right time is of prime importance in any FMCG company," suggesting that the value of AI is in making quicker, and more informed data-driven decisions. All respondents agreed on the fact that "Efficiency, which is reduce the time to insights" (R3) was a key motivating factor behind adopting AI to their business.

5.1.2 Increased Sales

In relation, a current theme of the interviews revealed time savings and revenue growth as a major component of the decision to adopt AI under the guise of bettering operational efficiency for incremental sales. For instance one respondent (R7) mentions "it is more of the effectiveness of the solution rather than the cost efficiency." Several of the companies implemented AI tools under this guise and perceived benefits in time savings to focus on what "humans still have, [which] is communication, planning, coordination, strategy, thinking, critical thinking.". Often, this perceived benefit was quantifiable, with one respondent (R2) stating that they "saved 96 hours per month per report per state … now focus[ing] on analysis and not making the report" and another (R3) mentioning that with the use of AI and data insights they were able to "reduce the time to insights for 80%," which frees up manual capacity and allows greater focus towards sales strategy. This idea is reiterated through the interviews and is stated simply in one of the interviews as if "I become more effective, I sell more products." (R7) It is clear that this aspect of AI in FMCG business processes is a key area of focus and a motivating factor for adopting such technologies. Additionally, systems were put in place in order to aid even frontline sales decisions in all cases, with one such system which is currently in use to "auto-generate the order for the store. … giv[ing] reasons like '7 stores in your neighborhood sell this well.'" (R7) Automation both in reporting and sales strategy is able to influence and support sales decisions, however it requires "bring[ing] together marketing, sales, and supply chain to make it work." (R5)

Another key proponent of the FMCG business and a main area of implementation of AI solutions throughout several of the interviews was that of the automation of on shelf availability, that is "how much space [they] are occupying and how much competitor space is being occupied in." (R8) On shelf availability is mentioned as "very, very critical to FMCG" and that models to track this were "articulated to the business" and eventually implemented. This has implications on ROI and sales as an "efficient AI based availability [will] generate more than 3 to 4% in incremental sales," (R3) which are significant figures in FMCG businesses and shows how AI tools can amplify commercial outcomes. Surmised, intelligent data insights and tracking with the use of AI solutions are able to generate time savings and incremental sales due to their efficiency gains and support in sales strategy decisions, which are a main proponent of the decision to adopt AI technology in FMCG business processes. This presents a business case for the organization and is a key motivating factor behind the decision to adopt AI across several FMCG companies.

5.2 Technological Factors for AI Adoption

Various approaches and levels of technological expertise to both build and implement AI technologies in-house were discovered throughout the interviews. The interviews revealed two main levels of technological expertise where the solution design, engineering, and implementation was either "most[ly] done in house," (R8) or that the "solution design [was] internal … then the engineering was outsourced to a partner." (R3) However, all interviewees mentioned along the lines of that when it comes to technological factors for adopting these solutions, "quality of data sets [is] #1" and that "any AI solution is only as present as the data it learns from." (R3) This theme of availability of data and quality of data was consistently reiterated throughout almost all interviews and could be summed up in the sentiment "AI can only work if the data quality is good." (R9) Several challenges were mentioned, such as that it is "in some parts of the business, data quality is better" (R7) or that the "master data was not good" (R8) and there was a lack of availability of quality data, especially for specific sectors or languages/dialects, causing issues "when the data was moved." (R1) Even in areas where data quality was high or abundant, it was often "still not brought to the level that would be readily available for adoption" (R7) or due to being "way too complex … datasets are not even there yet," (R3) which often led to the adoption of AI initiatives or the decision to do so being slowed or stopped by foundational data issues. Evidently, data is a technical asset for adopting AI technologies, however it can also be a strategic bottleneck, highlighting how it is essential to address its challenges in order to unlock value from these technologies.

Of course, when it comes to digital technologies, one respondent (R3) mentions that "digital leaders always push to have the best tech available, the right tech available," however through a business perspective they must also be "mutual to the business." This is a main balancing act, especially for leadership considering AI adoption. In terms of any potential barriers in the form of technological infrastructure and overall adoption rates a similar sentiment was shared, "it is not a challenge … [as] FMCG industries move very fast on this" (R3) and "technology adoption is high." (R7) Equally as important, infrastructure for centralized data storage and pipelines was noted as a key enabler in the decision-making process throughout the interviews, with "most of the companies hav[ing] moved to cloud technology" (R8) already to adopt cloud-based AI tools. This represents a similar starting point in terms of IT and infrastructure in most FMCG companies and of those interviewed. The main barriers come in the form of data quality, system integration as well as skilled technical workers for adopting AI solutions. For instance, the sentiment that it is "difficult to attract and retain talent" (R7) was mentioned´across several of the interviews (5/9 Respondents) with several stating that "[they] have been doing training" (R5) themselves instead, and one interviewee mentioning that they expect hires to have "60-70% of the skill" (R2) required. Additionally, with the move to cloud infrastructure people will need "to be able to operate in a cloud ecosystem, not just Excel." (R3) Currently, there seems to be a relatively high and shared level of infrastructure readiness and active technological adoption, even in regards to AI technologies in the FMCG industry within EMDEs, however some technological issues or lack of technical expertise for creating and adopting these technologies still persist, affecting the decision-making process for several of these firms to adopt further. Additionally, system integration limitations seem to be present across several of the companies, highlighted by one respondent (R3) noting that "there are few legacy systems, there are few new systems … integration issues will be there" and as surmised by another respondent (R7) stating "all three of them" - referring to lack of expertise, data quality, and system integrations as barriers to AI adoption.

5.3 Organizational Factors for AI Adoption

Organizational characteristics and resources play an influential role in the decision to adopt AI technologies within FMCG, with organizational culture and attitudes towards change, leadership mandates and budget control, and internal advocates and learning mechanisms being several dynamics affecting the decision-making to adopt AI technologies to the business. Whilst “the adoption of AI is more of a leadership decision” (R6) and “they are the ones giving the directives” (R6), in some cases AI initiatives emerged from within: “It was a lot of internal advocates… not a top-down decision.” (R7) Whilst much depends on the “leadership team or the leader of the business” (R6), with 7/9 respondents mentioning that “AI is a strategic priority,” much of the decision-making for any solution to be implemented comes down to determining if it will “help generate or increase sales” (R3). By “convinc[ing] the leadership that [they] need AI or need data …. as well as investing on that” (R3), the decision-making process regarding the adoption of such technologies can be sped up if the priority lies in adopting AI in their business. Additionally, as stated by one respondent “If I implement this right, I will gain efficiency… and because we have a high margin business, it by itself would fund the whole implementation” (R7). Reaching a broader organizational logic where AI is not merely a cost center but a strategic investment that pays for itself through operational gains would surely have implications on future decision-making regarding AI technologies.

A recurring theme throughout the interviews was the presence of opposition to or lack of readiness for change, whether it be “from people who are just worried about it because of the fear of their jobs … especially amongst middle management” (R3), there being “a lot resistance within the organization” (R9), such as an attitude expressed through one of the interviews that “whatever is working is working” (R8), or through demographics such as “the older people in the system would still have fear, you know” (R8) This speaks true for many of the companies within the FMCG industry as well as the companies in question, and “companies are investing money, especially on training people on AI” (R8) to reduce fears and build confidence that “the company is not backward looking. It is forward-looking and [they] are doing stuff” (R7) Additionally, “more training, more exposure” (R5) as well as “support from the top management” (R5), such as the need for the “freedom to fail … because not everything can be successful, so there has to be freedom to fail” (R8), were listed as part of the decision-making for adopting AI technologies, especially amongst employees less familiar with AI.

Organizational size and demographics play a role in decision-making for adopting AI technologies. For instance, regarding managing the change of disruptive technologies such as AI “It's easier for other companies with, like let's say 200 to 500 employees, but it's very difficult for companies who are like 500 employees” (R9). Additionally, “multinational organisations are quicker in implementing, but obviously because their budget pool is bigger and their talent pool is bigger” (R1) whereas “average organisations or country specific organisations, they are always a bit reluctant. They will be like my organisation. They will be very cautious in spending” (R1) Clearly, organizational characteristics play a role in the decision of whether or not to adopt AI. Another organizational demographics, as stated by another respondent: “there is a huge generation gap within the organisation … But sooner or later, when these newcomers like Gen Z would be part of the decision making or the making or the manager …. then that option would be much faster” (R8), reiterating the existing attitude of resistance to change and how a change in attitude or thought process may help speed up decision-making for AI adoption.

5.4 Environmental Factors for AI Adoption

The competitive environment surrounding the FMCG business as well as regulatory frameworks shape the way organizations approach AI and its adoption. Whilst it may not be intuitive initially, the “first adoption of the AI [was] actually not from the competition, it was actually from a problem" (R8) and since "most of the companies are structured in a similar way … the use cases would definitely be the same for most of them. The only difference would be from a brand perspective." (R8) Whilst competition does not play a direct role in the decision to adopt AI, several interviewees mentioned influence from success stories of other companies and the "need to keep an eye on what's happening outside." (R3) Staying informed on both competitors and vendors, firms can seek to learn from others in the industry which may ultimately prove to be a factor of which it influences their decision-making process to adopt AI.

AI can be described as an innovative and disruptive technology, and may well be impacted by national spending on innovation, especially in regards to "the support to the startup ecosystem." (R8) One respondent (R8) mentions the situation specifically in India where innovators within India "have to go and get fundings from outside of India … and then the stakeholders from those countries come down on board and then this whole innovation piece actually goes on out of India." This speaks to a lack of national spending on R&D and development work within India, which can correlate to a decreased talent pool and innovation as well as increased costs as these processes are going out of India which can impact decisions to adopt AI for companies operating nationally.

Regulatory frameworks/policy and its effects on decision-making for adoption of AI within FMCG is dependent on the countries of which the company operates in. Time lags of policy and differing regulations on data storage and privacy poses several bottlenecks for the decision to adopt AI within these companies. For example, one respondent (R3) mentioned if they are "consuming data for Vietnam business, [they] need to store it in a local server … [but they] might not have the capability" to do so "because [they] don't run a Vietnam business," meaning that their access to data may be hindered by local regulations, impacting their decision to adopt an AI solution for analysing data in that region. The respondent goes on to speak about a lack of understanding by government leaders regarding business concepts "the concept of cloud businesses or cloud infrastructure" as a contributing factor to these types of bottlenecks.

5.5 Future Outlook/Trends

Looking ahead, most interviewees expressed a strong belief in the long-term strategic value of AI in the FMCG sector. For instance, one respondent notes regarding the future outlook of AI in the FMCG industry: "The current frame of mind is positive… management wants to step into it. The industry is moving towards it and they believe they should as well" (R2). This falls in line with most interviews where AI was mentioned as a "strategic priority." Additionally, evidence to support this trend can be seen, particularly in markets like Singapore, Taiwan, and China where "a lot of heavy investment is going on… cloud data interests and AI startups are coming in with these solutions" (R3). Increased innovation investments for AI startups and infrastructure for these AI solutions will surely play a role in expanding the availability and adoption of AI tools within the industry and region.

Several respondents (6/9) also spoke to the increasing role AI is beginning to play within marketing and consumer experience: "where product innovation has natural limits, firms are turning to AI to innovate in how they engage consumers." (R9) One respondent (R4) notes "reaching the consumers the way we want is largely dependent on the kind of trends and the things that people are moving towards, and AI is becoming that core part," showing how AI is becoming increasingly embedded in marketing and for strengthening consumer experience, key factors related to the FMCG industry. Additionally, this shift in marketing and consumer engagement strategy and processes towards AI is described by one respondent through:

It is noted by one respondent (R3), regarding current data localization challenges related to the adoption of AI, the belief that "in a couple of years … we'll be in a much better situation to handle this localization," which shows an optimistic stance regarding current data access and quality issues impacting adoption of AI. Overall, the trend for the FMCG industry, both globally and within EMDEs, and in regards to adoption of AI, is that the use case for AI is expanding towards a multitude of business processes and technological infrastructure to support its adoption seems to be improving in the right direction.

6. Analysis

6.1 Introduction to the Analysis

The core research question: How are the key technological, organizational, and environmental factors influencing the decision to adopt artificial intelligence in fast-moving consumer goods (FMCG) companies within emerging markets? is situated within the broader context of digital transformation and AI's role in business model and process innovation through the lens of the TOE framework which provided a structured framework of which to view the factors playing a role in the decision-making and adoption of digital transformations or AI technologies.

Qualitative interviews with key stakeholders, all currently present and operating within emerging markets, and with expertise regarding the topic of AI and adoption, and the TOE framework were employed to explore the factors influencing AI adoption in FMCG firms operating within emerging markets.This methodological approach helped uncover insights into both the barriers and drivers of decision-making for AI adoption as well as the motivation to first adopt AI and the future outlook of AI Adoption and its decision-making in FMCG businesses in emerging markets. A thematic approach was used to draw influencing factors which presented themselves throughout the interview responses and accompanying analysis.

6.2 Technological Factors

Perceived Compatibility: Responses uncovered a differing degree towards how AI was perceived as aligning with the business needs of FMCG companies, with most describing high degree of alignment, particularly in regards to supply chain management and sales and marketing as well as the importance of balancing budget for technological infrastructure and data investment requirements with expected return. AI was generally seen as a tool to enhance operational efficiency and as a driver of sales or sales strategy, rather than as a standalone solution. This, too, aligns with findings (Foradellas, 2021) regarding the potential for AI technologies to improve operational efficiency, boost sales and improve consumer outcomes.

Perceived Relative Advantage: There are relative, quantifiable, advantages of AI adoption as discovered through the responses, particularly in improving operational efficiency through report automation, in turn reducing costs, as well as enhancing sales and marketing efforts through AI-generated content creation and data-driven sales insights. These advantages were central to the adoption decision, reinforcing the findings in previous studies that suggest that the increased efficiency, accuracy, and reduced operational costs (Ramdani et al., 2009) are key drivers in AI adoption and that AI must deliver clear, tangible benefits for successful adoption (Yang et al., 2015; Wang et al., 2010).

Technology Resources: Data availability and data quality plays an increasingly large role in the decision to adopt AI, and numerous languages and dialects present in emerging markets where these multinational FMCGs operate also play a role in the quality of data that is able to be obtained. While data availability was essential, the lack of structured, usable data often posed challenges during or before the implementation phase. Whilst not a core component of the TOE framework, technology resources, particularly in terms of data availability and quality, are increasingly relevant towards the FMCG industry and its adoption of AI, especially in terms of generating data-driven insights.

Technology Readiness: There are varying levels of preparedness of organizations in terms of technological infrastructure and skilled workforce, however with quite high rates of technology adoption in general. While FMCG companies may not have had extensive AI expertise initially, they leveraged existing technological readiness to support the integration of AI. Additionally, the emergence of cloud storage services and infrastructure have pushed decision-making towards adopting cloud-based AI tools, which are becoming increasingly prevalent. This, in turn, decreases the perceived complexity which is, as noted by Rogers (2003), negatively related to the rate of adoption.

6.3 Organizational Factors

Presence of Internal Change Agents: The analysis shows that AI adoption in FMCG companies was often initiated by individuals within the organization who understood the potential benefits of AI and were able to campaign and communicate their vision for its integration, despite the broader organizational challenges or reluctance. This falls in line with what Howell and Higgins (1990) concluded in that the internal champions enthusiasm for the proposed change can create the commitment of said change in others, namely in this case the decision-makers or top leadership.

Top Management Support: Top management played a vital role in supporting AI initiatives as well as to ensure adoption throughout the company. While it was often employees who initiated the process, the final push or directive to adopt AI came from top management, who provided resources and support such as training and upskilling initiatives as well as strategic direction, mostly in the aim of finding relevant solutions to their current problems. This support from management was found to be indeed critical in driving adoption of new technologies (Hsu et al., 2019) such as AI,

Organizational Size: Larger FMCG companies had the resources to support AI initiatives, both in that they were able to allocate more resources towards it and were able to "fail" more often, while smaller firms were often more agile but lacked the same financial capabilities. This correlates with the idea that larger organizations have more resources and capacity, and thus are better equipped to adopt, implement, and then scale new technologies (Aboelmaged, 2014).

6.4 Environmental Factors

Competitive Pressure: External market pressures did not necessarily shape the decision to adopt AI, however with FMCG firms facing similar problems and inefficiencies and with AI as a viable use case to solve some of these issues, competition indirectly affected these decisions to adopt AI technologies or innovate themselves. The FMCG sector similarly faced pressure to adopt AI in order to remain competitive and not fall behind competitors. However, the intensity of this pressure varied across firms depending on their market position and technological maturity as well as organizational goals. This falls in line with findings that high levels of competition within an industry drives the need for innovation, leading to the adoption and implementation of many new technologies (Zhu et al., 2003).

Regulatory Environment: The legal and regulatory landscape, particularly around data privacy and storage as well as internal and external policy regarding AI ethics had a varied impact on how FMCG companies approached AI adoption or at least the feasibility of doing so. Namely, there seems to be a lack of expertise and know-how amongst the current policy-makers which in some cases hamper the ability to create innovative solutions or store data locally within some regions as a result of not up-to-date regulation/policy. Regulatory frameworks within the region of study could be described as less developed than in other regions such as the USA or Europe, and in some cases this can act both as an enabler and a constraint depending on the country and the sector.

Market Infrastructure: There are significant infrastructure constraints that impact AI adoption in emerging markets, such as access to high-quality data, computing power, and data storage solutions. However, almost all large corporations within these emerging markets use AI at least to some degree. The market infrastructure was a critical factor in determining the feasibility and scope of AI applications in FMCG companies within EMDEs, and certainly played a role in the decision to adopt AI and to what extent for these companies.

6.5 Task Optimization

Task Complexity: AI adoption is closely linked to the complexity of tasks within FMCG organizations as well as the degree of skill required in certain working roles. AI was adopted to manage complex, previously very manual, tasks related to data analysis, demand forecasting, and reporting insights. However, the inherent complexity of tasks remained, with AI acting as a facilitator, or a “middle-man” rather than a complete solution. The findings were centered around freeing up manpower as well as time which could be allocated to more strategic tasks.

6.6 Summary of Key Findings

By coding all transcripts from the interviews under 5 in-scope parent codes relevant to empirical data collected from the interviews, key findings and their relative weight were uncovered through an analysis of related terms under the parent code and how many times they showed up across interviews. This provided us with a measurable method to categorize themes and findings into several sub-sections or child code.

Motive for Adoption: Efficiency and Cost savings proved the most apparent theme within the category motive for adoption of AI technologies across the companies and interviews, followed by Data-driven insights and Speed and Scale in Marketing Content. This represents the key motivating factors uncovered of which influence adoption of AI technologies

Technological Factors: Data availability and quality proved the most apparent theme alongside legacy-system integration and cloud-ready infrastructure, as key influencing factors for AI adoption from a technological standpoint .

Organizational Factors: Leadership mandate and budget control proved the most apparent theme followed by Skill and Upskilling and Internal Champions as factors related to the organization which influence decision-making for AI adoption throughout the interviews and within the companies.

Environmental Factors: Data-sharing partnerships proved the most apparent theme alongside competitive pressure and data localization for the key findings under the environment, both internal and external, of which impact decision-making to adopt AI technologies.

Future Outlook: Workforce re-design and training at scale proved the most apparent theme in regards to future outlook or trends surrounding the FMCG business and AI adoption and decision-making. This was accompanied by Ecosystem Optimization and Responsible AI and governance frameworks.

The main technological, organizational, and environmental factors that influenced AI adoption in FMCG companies as well as the motive for adoption is as summarized in the chart below and is separated into sections by color and subsections through smaller boxes within the main sections. The numerical reference hits provided from each section and subsection are categorized by size with the largest boxes corresponding to the most reference hits throughout the interviews and the shading of the subsections representing the amount of reference hits within each main section or parent code with the darker sections corresponding to more reference hits in the texts and the more transparent sub-sections corresponding to lower reference hits throughout the text:

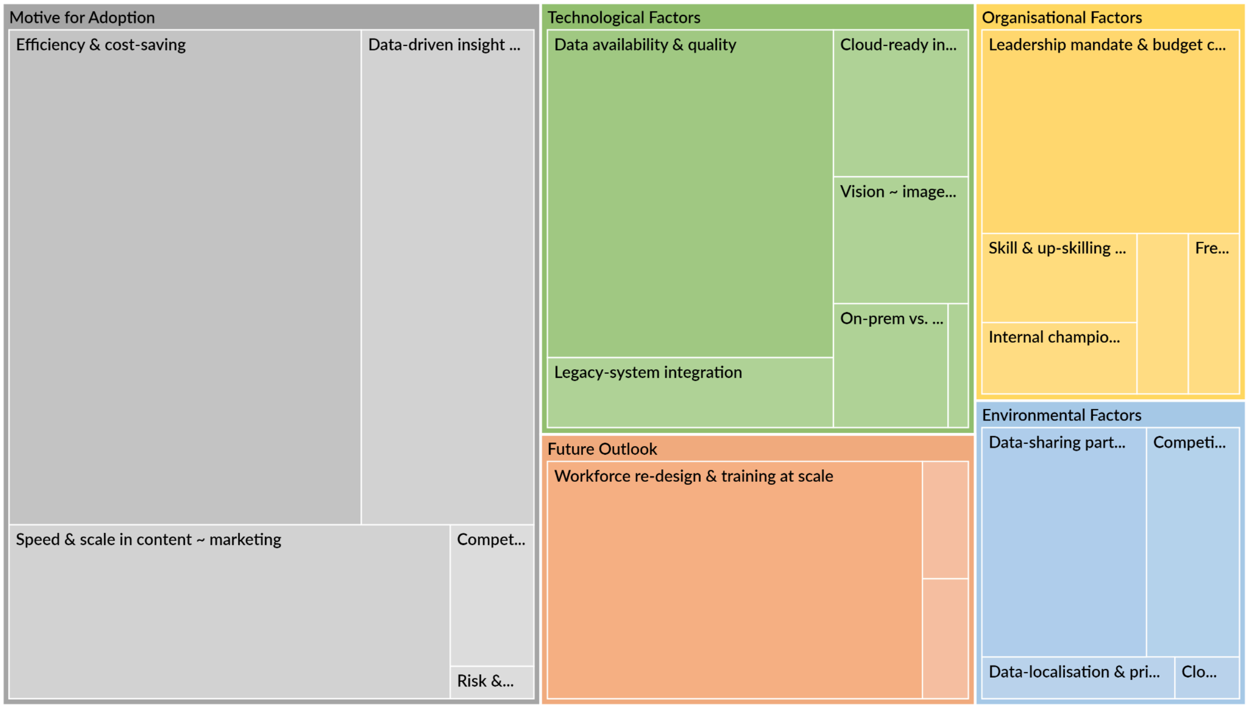


fig 3: code query matrix showing most frequently mentioned child codes sorted into parent codes

From these key findings and with combination through the lens of the TOE framework, a sentiment analysis was done on whether or not these factors influenced the decision to adopt AI in a positive (increased) or negative (decreased) way. The findings are as summarized below:

Technological factors: Lack of data quality (decreased), access to technological expertise (decreased in some cases, increased in some), technological readiness/infrastructure (increased)

Organizational: Financial constraints (decreased), knowledge/attitude gap (decreased in some cases, increased in some), reliance on results/outcomes for decision-making regarding further AI adoption (increased), job security/skepticism (decreased), access to skilled labor (decreased), training/upskilling (increased)

Environmental: Policy/regulation (increased in some decreased in others), national expenditure (decreased), competition (increased indirectly)

7. Discussion and Conclusion

7.1 Answering the Research Question

7.1.1 Technological Factors

Perceived compatibility and relative advantage, were decisive in AI adoption and the decision from top management (most decisions came from top-down) to allocate resources towards adopting or building AI solutions. In the three cases investigated AI tools were able to be integrated into existing ERP systems or legacy systems were changed. When managers see the compatibility of the new technology with existing infrastructure, and when the change can promise quick wins, such as saving 96 hours per month (Company 1) they are incentivized to make the decision to adopt AI. The single largest hurdle for technological factors was data quality, with all firms having some issues regarding data. This issue needs to be resolved as data quality is the most important attribute in order to generate data-driven insights.

7.1.2 Organizational Factors

All three firms communicated that AI adoption was a strategic priority for management.Organizational size played somewhat of a role, however, top management support and the presence of business use cases were the most crucial for driving AI adoption decisions. The leadership's role in resource allocation and strategic alignment was a consistent theme across the FMCG firms explored. Additionally, change management strategies and leadership support through training and upskilling initiatives aided in reducing resistance to change, and in totality aided the decision to adopt AI.

7.1.3 Environmental Factors

Competitive pressure and regulatory considerations played varying, firms were generally aware of competitor actions but moved to adopt AI to solve firm specific pain points. Their influence varied depending on the company's market position and the regulatory environment in which it operated, with most reporting that the regulatory environment was not yet up to speed, whilst some reported serious bottlenecks for AI adoption decisions as a result. Additionally, fostering innovation and a skilled talent pool through national investments hindered this process within EMDEs as start-up ecosystems and national spending on R&D were lower than OECD peers.

7.2 Comparison with Existing Literature

As discussed in the literature review, the three most influential factors that show up regardless of geography and industry type are, clear business benefits, usable quality, and support from top management. The findings of this study align mostly with existing literature on AI adoption however it brings up a few challenges to previous research which is not centered around the FMCG industry, especially in regards to technological readiness and infrastructure requirements. Unlike the global survey, which found that companies first tackle infrastructure issues and then culture, within the study we found that the organizations were handling this simultaneously. This is mainly due to data quality issues. This could point to a trend amongst FMCGs operating in EMDEs, where there is a gap in the IT infrastructure readiness as compared to OECD counterparts.

7.3 Implications for Theory

This study broadens the application of these models in the context of AI adoption and sheds light on factors previously underexplored in the literature. This is due to the evolving and complex nature of AI and digital technologies which could propose an alternate theory or additions to the existing TOE theory, specifically in the technological factors to better fit these recent technological developments. The technological factors contain data readiness, however looking at the effect data readiness has on the adoption we believe it is more prudent to make this its own first-order influencing factor, distinct from IT infrastructure, which remains under technological factors. Secondly, a bottleneck facing all FMCG companies is lack of talent, specifically lack of technical expertise. This dimension could also be added as a first-order influencing factor, as we have observed that this caused 2 out of 3 companies to outsource most of the development.

7.4 Limitations of the Study

There are three main limitations; sample size, lack of end-user input, and reduced access to non-verbal communication. The sample size, comprising three FMCG companies, limits any statistical generalization and only allows for analytical generalization. The lack of end-user input as well as a lack of input from less senior employees means that the analysis might not be able to go into deeper detail regarding the nuances of working flows and different potential AI adoptions and their effect on these disturbances. Finally, all meetings were conducted online, and some interviewees had their camera off, this meant that non-verbal cues and communication could not be captured. Another limitation of the study is the rapidly evolving regulatory landscape, which might render some observations obsolete as governmental policy catches up with innovation.

7.5 Suggestions for Future Research

For future research direction, studies focusing on AI adoptions decisions in a different industry type, or within FMCG but in another geographical region. Furthermore, the study can be expanded to look at long-term impacts of AI implementation, could then focus more on upskilling and training, end-user perspectives, and employee perception on AI, while also exploring whether long term AI improves organizational performance or provides a competitive advantage. Finally, a study conducted in a few years would also have more readily available KPIs which can be standardised across different organizations, this could allow for a qualitative approach to be taken, thereby allowing for statistically generalizable findings to be made.

8. Implications for Practise

As discussed in the methodology, while we cannot use the results of this study for a statistical generalization, it can be used for analytic generalizations. The five overarching parent codes uncovered offer a guidebook for FMCGs who are trying to convert the hype around AI into low-risk easy-win projects that demonstrate profitability and increase efficiency. As this study is centered around EMDEs, where talent is not as abundant as OECD counterparts, and margins are tighter, managers must know how to approach the process of AI adoption. Otherwise they risk the project becoming a pilot program that dies out quickly, without being able to scale and demonstrate value to stakeholders. The authors have identified three stakeholder groups (managers, supply-chain partners, and regulatory bodies) for whom these practical implications form actionable insights. And by acting on them, firms can start to bridge the adoption gap that is emerging between EMDEs and OECD countries.

8.1 Practical Implications for Managers

8.1.1 Strategic Actions

When viewing AI adoptions in the organization, it is important to spread out the risk by having a few easy-win projects alongside one data-heavy more long-term project. Easy-win projects such as content generation for marketing and sales channels, sales report generation, or a quality checks system, these applications of AI are not difficult to implement and can show their effect on efficiency and costs quickly. This inturn builds confidence amongst key decision makers in the organization, allowing for resource allocation and capital allocation towards the long-term initiatives. Additionally, for managers looking to act as internal advocates (change agents), publishing a roadmap showing the different initiatives helps to push through skepticism, as well as create more accountability as the plan is visible to all.

8.1.2 Operational Level Changes

In order to increase the likelihood of success, managers need to build cross-functional AI teams within existing team structures. This team should have both employees who have the technological capabilities to spearhead the integration as well as a domain expert (expert in the business function where adoption is occurring) who can identify and communicate pain points in their workflows. This should also be complimented with a third employee type the “translator”, one who has the technological understanding and the domain expertises, this employee will act as a go between. This type of team will not only be able to recognise pain points that can be solved using AI application, but also be able to create pilot programs with greater efficiency and accuracy as compared to a standalone team coordinating with different business functions.

8.1.3 Upskilling and Protecting Internal Advocate

Through our investigation, we found that the segment of employees most fearful about AI are mid-level employees. This is due to two main factors, firstly any repetitive tasks or tasks not requiring much human intervention can be outsourced to AI. Secondly, there is a lack of knowledge on how to effectively use AI in conjunction with own-capabilities to be more efficient. To this end offering upskilling initiative to all employees, having a robust internal AI policy, and providing employees with a prompt library can be actions taken to mitigate fearful employee perceptions. Additionally, if the internal advocate (champion) is expected to perform their job role while also spearheading the change, this can lead to burnout and subsequent turnover. To mitigate this, if top management sees merit in the advocates' ideas they should act to protect the champions and provide them with enough resources and capabilities to succeed.

8.2 Practical Implications for Supply-chain partners

An issue noted for organizations operating in a B-2-B context (selling to a distributor who then sells to the wider market) there have been issues regarding data quality. These mainly stem from data quality being poor and distributors not sharing valuable customer data. A work around would be to offer a quid pro quo supplying them with insights collected on market and sales promotions in exchange for the raw point-of-sale data. This would benefit both parties and allow them both to increase data-driven decision making within their firms. Additionally, in areas where both parties can utilize the AI application, splitting pilot costs with top partners is a useful strategy. This allows the organization to reduce supply chain noise, therein positioning the firm to recoup the investment. Finally, standardising SKU names, date formats, and other related codes across all partners can help improve data quality, and drive more data-driven decision making.

8.3 Practical Implications for Regulators

Within emerging markets regulators need to balance the want for increased innovation with the need for data privacy. To this end, creating an AI sandbox, de-identified data made available for organizations to train their models, can help to balance out these two conflicting wants and needs. Additionally, as AI adoption grows in the region, regulators across APAC must cooperate to decrease overall compliance costs. This in turn will drive more cross-border data flows and innovation, and therefore should be balanced out with a GDPR style data protection law.

8.4 Implications for Society

Amongst consumers there is a rising awareness about the usefulness of personal data, with many consumers being vary of their data being used without their consent. As such publishing information such as what data the model is collecting and trained on, how often the model is retrained on a new data set, and offering a contact for any queries surrounding the organizations use of AI, can help to build trust with consumers. This transparency can work to alleviate consumer concern as well as acting as a differentiator from competitors. Additionally, offering upskilling initiatives (see 9.1.3) not only allows the company to create the “translator” employees (see 9.1.2) but also increase the overall understanding of AI and its many uses. Finally, having an internal data-ethics group can help to boost trustworthiness. This group would publish quarterly reports going over the company's use of data and its compliance with regulations. All of these implications act to increase consumer and employee trust, which can have positive effects on sales.

8.5 Limitations of Implications

This study investigates three FMCG companies within the APAC region, and the interviewees were all senior-level employees. This was done as the nature of organizations in this region means that lower and mid-level employees would not be as privy to details surrounding the decision to adopt AI. They would be aware of any official company communication, but would not be able to speak to future plans. Additionally, the companies are all mid-large in size and revenue. A small mom and pop store which does not have an existing ERP system would have a hard time creating a demand forecasting application. Finally, the two companies operating in multiple geographies mainly used data from B-2-B activities (i.e. no personal data). The company operating in India did use personal data however they only have to adhere with Indian regulation surrounding data privacy and protection. As such for an organization operating in multiple geographies and utilizing personal data would not be able to utilize some of the implications mentioned.

8.6 Implementation Road Map (18 months)

Month	Tasks	Expected outcomes (wins)
0 - 4	● Audit data silos to understand any data quality issues ● Build out cross-function AI teams. Start with the team related to the easy-win application	Data gaps become visible and team is in place
5 - 9	● Launch the easy-win pilot ● Run upskilling workshops ● Build out team for longer term application and begin laying the groundwork for the pilot	Demonstrate cost-saving potential, use it as a case for larger rollout/more data intensive pilot. Upskilling helps to alleviate employee concerns
10 - 14	● Measure results of easy-win pilot, launch longer term more data intensive application ● Continue run upskilling workshops, complemented by prompt libraries (if GenAI) or create internal AI usage policies ● Negotiate with partners for data sharing	Proof of concept, and begin to entice partners to buy-in
15 - 18	● Scale pilot programs ● Publish reports to increase trustworthiness ● Use data on success to convince partner to split costs, convince other stakeholder to assign more resources and capacity	Broader roll out, capture trustworthiness in the market

9. References

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. International Journal of Information Management, 34(5), 639-651.

Ångström, R. C., Björn, M., Dahlander, L., Mähring, M., & Wallin, M. W. (2023). Getting AI implementation right: Insights from a global survey. California Management Review, 66(1), 1–18.

Benfratello, L., & Shiqian, L. (2021). Strategic operations management in FMCG: A comprehensive review of best practices and innovations. ResearchGate. https://www.researchgate.net/publication/379229256_STRATEGIC_OPERATIONS_MANAGEMENT_IN_FMCG_A_COMPREHENSIVE_REVIEW_OF_BEST_PRACTICES_AND_INNOVATIONS

Bengio, Y., Goodfellow, I., & Courville, A. (2017). Deep learning (Vol. 1, pp. 23-24). MIT Press.

Chong, A. Y. L. (2009). Factors affecting the adoption level of c-commerce: An empirical study. ResearchGate. https://www.researchgate.net/publication/237063138_Factors_affecting_the_adoption_level_of_c-commerce_An_empirical_study

Dedrick, J., & West, J. (2003). Why firms adopt open source platforms: A grounded theory of innovation and standards adoption. ResearchGate. https://www.researchgate.net/publication/239184573_Why_firms_adopt_open_source_platforms_A_grounded_theory_of_innovation_and_standards_adoption

Exploring supply chain agility in the FMCG industry. (2021). ResearchGate. https://www.researchgate.net/publication/352273302_Exploring_supply_chain_agility_in_the_FMCG_industry

Foradellas, R. F. (2021). Digital transformation and artificial intelligence applied to business: Legal regulations, the ethical factor, and recommendations. Laws, 10(3), 70. https://www.mdpi.com/2075-471X/10/3/70

Gangwar, H., & Raoot, A. D. (2013). Review on IT adoption: Insights from recent technologies. ResearchGate. https://www.researchgate.net/publication/275316263_Review_on_IT_adoption_Insights_from_recent_technologies

Grover, V. (1993). An empirically derived model for the adoption of customer‐based interorganizational systems. Decision Sciences, 24(3), 603-640. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5915.1993.tb01295.x

Howell, J. M., & Higgins, C. A. (1990). Champions of technological innovation. Administrative Science Quarterly, 35(2), 317-341.

Hsu, H., Liu, F., Tsou, H., & Chen, L. (2019). Openness of technology adoption, top management support and service innovation: A social innovation perspective. Journal of Business & Industrial Marketing, 34(3), 575-590.

Ikpe, E. (2024). Artificial intelligence adoption in manufacturing: Organizational factors and performance implications. Journal of Health and Allied Sciences, 8(1). https://dx.doi.org/10.4314/johasam.v8i1.3

Jain, V., Tewary, T., & Gopalakrishnan, B. N. (2021). Unlocking technology adoption for a robust food supply chain: Evidence from Indian food processing sector. HSE Economic Journal, 25(1), 147–164.

Lee, S. (2023). Digital transformation and AI adoption in supply chain management. Journal of Business Research, 158, 113642. https://www.sciencedirect.com/science/article/pii/S0378720623000642

McKinsey & Company. (2023). Survey: AI adoption proves its worth, but few scale impact. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Meotto, M. (2021). A case study of digital transformation in the FMCG industry [Master's thesis, Politecnico di Milano]. https://www.politesi.polimi.it/bitstream/10589/173721/1/2021_4_Meotto.pdf

Mubarok, A., & Sari, R. (2021). Comparative study of artificial intelligence (AI): A literature review. Semantic Scholar.

Westerman, G., Bonnet, D., & McAfee, A. (2014). The nine elements of digital transformation. MIT Sloan Management Review, 55(3), 1-6.

Nozari, H. (2021). AI implementation challenges in supply chain management. International Journal of Innovation in Management, Economics and Social Sciences, 1(2). https://ijimes.ir/index.php/ijimes/article/view/18

OECD. (2023). A portrait of AI adopters across countries. https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/04/a-portrait-of-ai-adopters-across-countries_76004dec/0fb79bb9-en.pdf

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. Electronic Journal of Information Systems Evaluation, 14(1), 110–121.

Olufemi-Phillips, A. (2024). Technology adoption in emerging markets. International Journal of Management and Entrepreneurship Research, 6(3). https://www.fepbl.com/index.php/ijmer/article/view/1689

Ramdani, B., Kawalek, P., & Lorenzo, O. (2009). Predicting SMEs' adoption of enterprise systems. Journal of Enterprise Information Management, 22(1), 10-24.

Rodríguez, N. G., Pérez, M., & Gutiérrez, J. A. T. (2008). Can a good organizational climate compensate for a lack of top management commitment to new product development? Journal of Business Research, 61(2), 118-131.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Rossman, B. (2018). Digital maturity: Conceptualization and measurement model. ResearchGate. https://www.researchgate.net/publication/345760193_Digital_Maturity_Conceptualization_and_Measurement_Model

Russell, S., & Norvig, P. (2016). Artificial intelligence: A modern approach. Scientific Research Publishing. https://www.scirp.org/reference/referencespapers?referenceid=2487817

Sharma, M., Sehgal, S., & Daim, T. (2022). Technology adoption readiness index (TARI) framework for FMCG companies. Technological Forecasting and Social Change, 174, 121201. https://www.sciencedirect.com/science/article/pii/S2444569X22001160

Strategic operations management in FMCG: A comprehensive review of best practices and innovations. (2023). ResearchGate. https://www.researchgate.net/publication/379229256_STRATEGIC_OPERATIONS_MANAGEMENT_IN_FMCG_A_COMPREHENSIVE_REVIEW_OF_BEST_PRACTICES_AND_INNOVATIONS

Sugathan, P., Ranjan, K. R., & Mulky, A. G. (2018). An examination of ERP-integrated services and supply chain flexibility. European Journal of Marketing, 52(7/8), 1549-1575. https://www.emerald.com/insight/content/doi/10.1108/ejm-04-2016-0228/full/html

Thong, J. Y. L. (1999). An integrated model of information systems adoption in small businesses. ResearchGate. https://www.researchgate.net/publication/220591627_An_Integrated_Model_of_Information_Systems_Adoption_in_Small_Businesses

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). The processes of technological innovation. Lexington Books.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. IEEE Transactions on Engineering Management, 29(1), 28-45.

Trillo, P. (2023). Benefits and barriers of chatbot use in education. In Technology curriculum 2023. Pressbooks. https://pressbooks.pub/techcurr2023/chapter/benefits-and-barriers-of-chaptbot-use-in-education/

Wang, Y., Wang, Y., & Yang, Y. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting & Social Change, 77(5), 803-815.

Weber, F., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. Digital Policy, Regulation and Governance, 21(3), 264-279.

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. Technological Forecasting and Social Change, 201, 123251. https://doi.org/10.1016/j.techfore.2024.123251

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. Computers in Human Behavior, 45, 254-264.

Yin, R. K. (2018). Case study research: Design and methods (6th ed.). SAGE.

Zhu, K., Kraemer, K., & Xu, S. (2003). Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. European Journal of Information Systems, 12(4), 251-268.

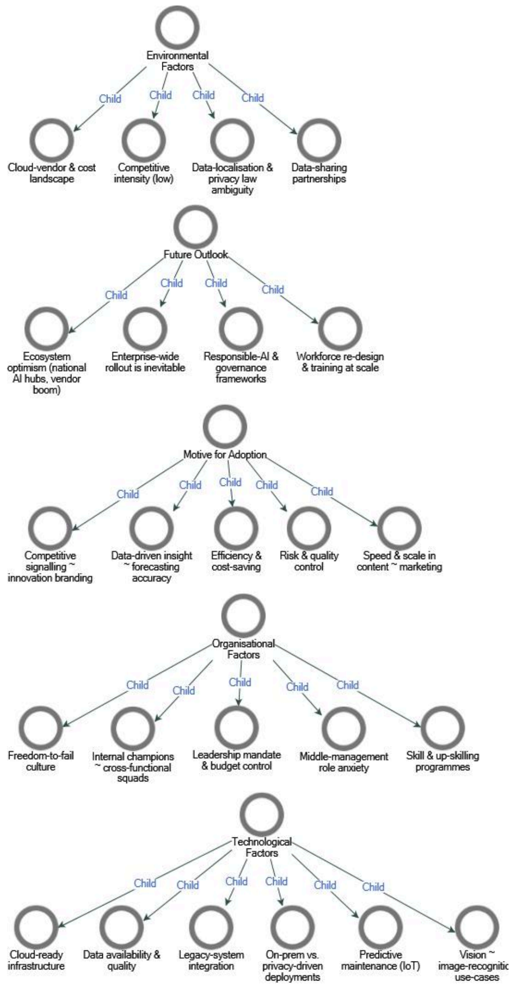
10. Appendix

Appendix A - AI use cases in FMCG

The key challenges FMCG companies face within their operations, as supported by evidence from several sources, can be summed up into three distinct challenges: Demand volatility, short product life cycles, and complex supply chains (Eltawy & Gallear, 2021, Meotto, 2020, Pannu, 2021). These challenges, as well as the core business activities of FMCG companies span across a variety of sectors. Namely: Retail, Transportation, Manufacturing, and Finance. These processes can in some degree replace human workload or be supplemented through the implementation of AI in these processes. For example, some relevant applications to the business processes of FMCG companies include (Ikpe 2024):

- **Machine Learning and Predictive Analytics:** Advanced forecasting techniques that can improve the accuracy of their demand forecasts, ensuring lean management practices.
- **Automation:** Automating essential data-intensive and modular business processes such as order fulfillment, inventory management, and production with technologies such as machine learning algorithms, robotics and automated conveyors can help FMCG companies increase production speed, reduce errors, and improve quality control.
    - **Inventory Management Software:** Machine Learning algorithms track inventory levels in real-time and identify opportunities for further inventory reduction. Inventory Management Systems such as Just-In-Time (JIT) inventory ensures inventory is only replenished when it is needed, i.e when there is consumer demand. Alternatively, RFID tags can be used to track inventory real-time and automatically reorder when inventory levels are low.
    - **Advanced Analytics and Robotics for Production Management:** Machine Learning algorithms for production planning and scheduling practices in FMCG operations: advanced planning tools, enterprise resource planning (ERP) systems, and advanced analytics for production optimization. Effective practices can help FMCG companies meet customer demand, reduce lead times, and improve operational efficiency. Additionally, modular production processes being done manually can be replaced with robotics in order to meet high, often-changing customer demands.
- **AI-Chatbots for Customer Recommendations and Marketing:** AI Chatbots with personalized recommendations based on customers historical purchases can be used to improve customer engagement. Additionally, marketing efforts can be tailored with the use of machine learning algorithms that analyze trends on social media and retail stores. For example, this can aid marketing campaigns and placement of products to improve reach and probability of purchase.
- **AI-Chatbots for Customer Service:** Automating tasks that are repetitive or simply answered through a knowledge base accessible through machine learning can aid in decreasing workflow and labor costs for service workforce.

Appendix B - Parent and Child Codes that we fed the in-vivo codes into

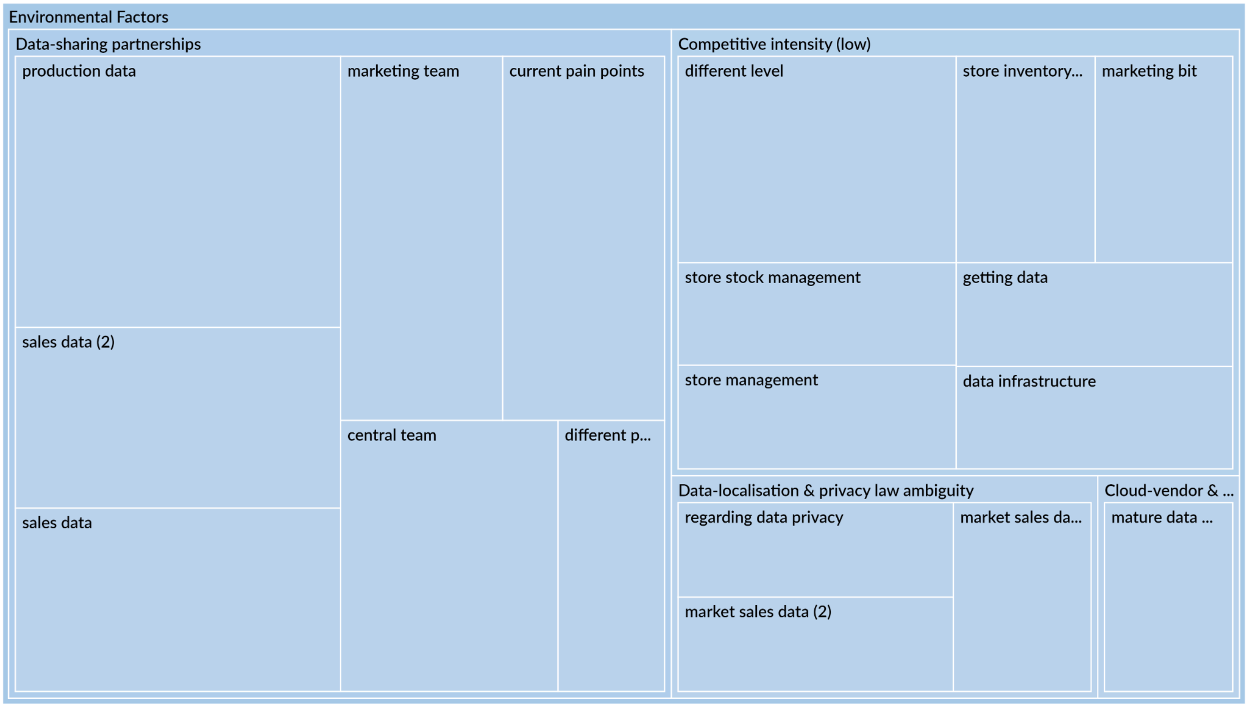

Environmental Factors
Cloud-vendor & cost landscape
Competitive intensity (low)
Data-localisation & privacy law ambiguity
Data-sharing partnerships
Future Outlook
Ecosystem optimism (national AI hubs, vendor boom)
Enterprise-wide rollout is inevitable
Responsible-AI & governance frameworks
Workforce re-design & training at scale
Motive for Adoption
Competitive signalling ~ innovation branding
Data-driven insight ~ forecasting accuracy
Efficiency & cost-saving
Risk & quality control
Speed & scale in content ~ marketing
Organisational Factors
Freedom-to-fail culture
Internal champions ~ cross-functional squads
Leadership mandate & budget control
Middle-management role anxiety
Skill & up-skilling programmes
Technological Factors
Cloud-ready infrastructure
Data availability & quality
Legacy-system integration
On-prem vs. privacy-driven deployments
Predictive maintenance (IoT)
Vision ~ image-recognitio use-cases

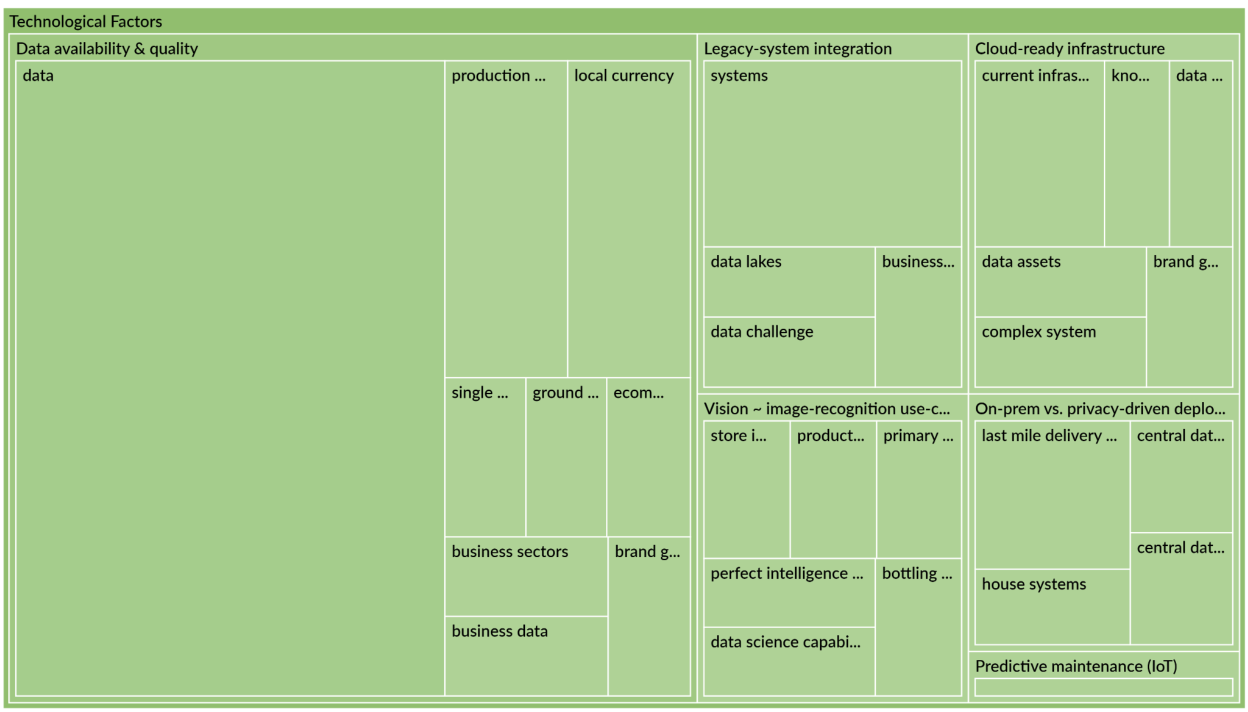
Appendix C: Frequency analysis table showing which child and parent was mentioned most

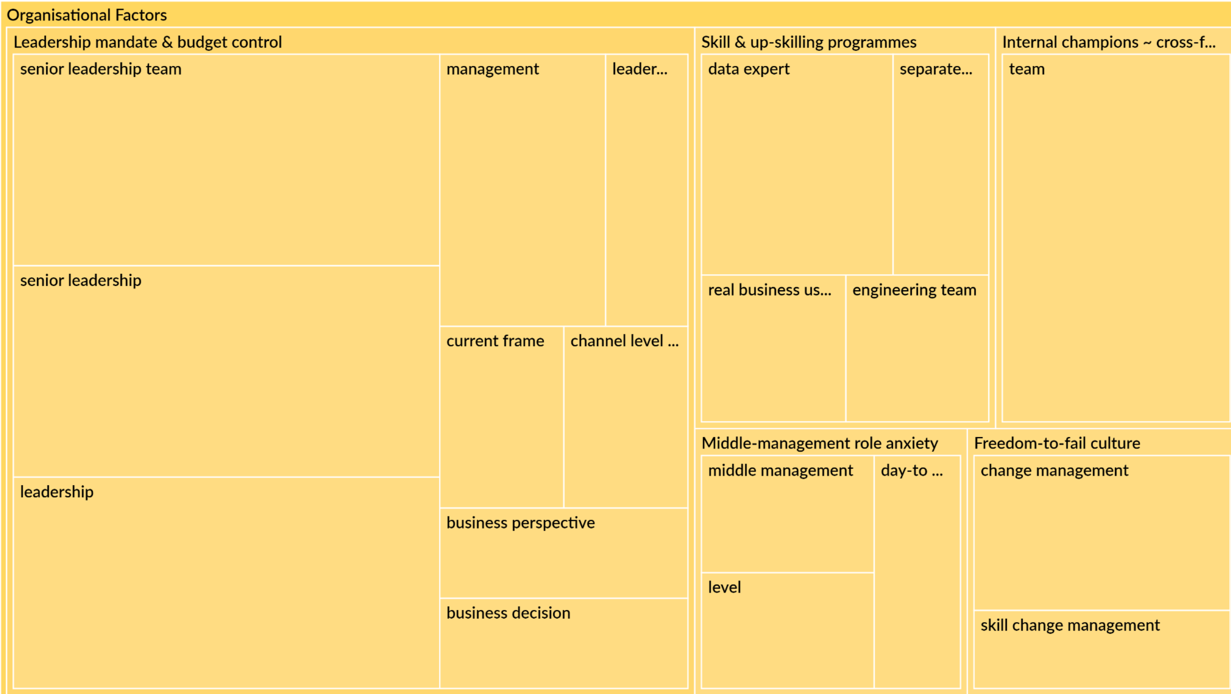
Column 1	D : R1	A : R2	E : R3	H : R4	F : R5	I : R6	G : R7	C : R8	B : R9
25 : Environmental Factors	2	2	3	0	3	3	3	1	2
1 : Cloud-vendor & cost landscape	0	0	1	0	0	0	0	0	0
2 : Competitive intensity (low)	0	1	1	0	1	0	2	0	2
3 : Data-localisation & privacy law ambiguity	0	0	0	0	0	1	0	1	0
4 : Data-sharing partnerships	2	1	1	0	2	2	1	0	0
26 : Future Outlook	3	2	8	3	5	4	0	6	1
5 : Ecosystem optimism (national AI hubs, vendor boom)	0	0	2	0	0	0	0	0	0
6 : Enterprise-wide rollout is inevitable	0	1	0	0	0	1	0	0	0
7 : Responsible-AI & governance frameworks	0	0	0	0	0	0	0	0	0
8 : Workforce re-design & training at scale	3	1	6	3	5	3	0	6	1
27 : Motive for Adoption	3	6	10	6	5	16	12	18	17
9 : Risk & quality control	0	0	0	0	0	0	0	1	0
10 : Efficiency & cost-saving	1	5	4	1	3	11	6	9	9
11 : Data-driven insight ~ forecasting accuracy	0	2	4	0	2	3	3	6	4
12 : Speed & scale in content ~ marketing	2	2	1	5	2	2	3	5	3
13 : Competitive signalling ~ innovation branding	1	0	1	0	0	0	0	1	1
28 : Organisational Factors	2	2	4	2	1	6	2	5	2

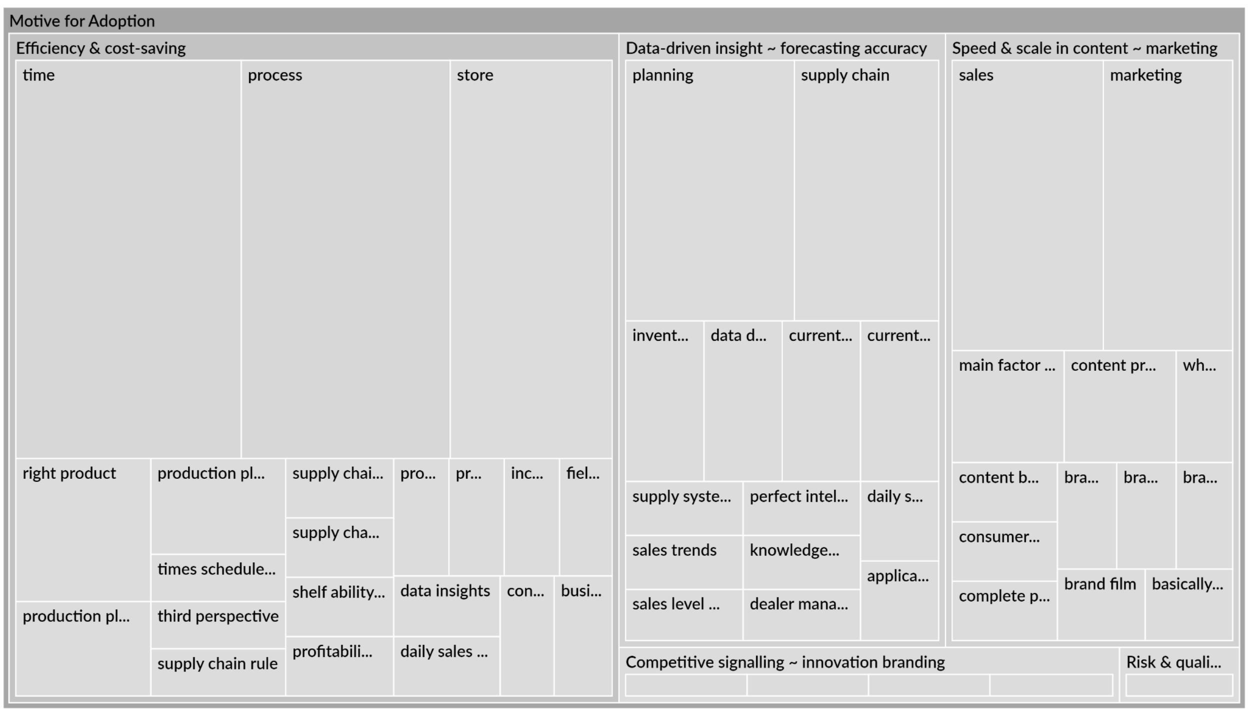
14 : Freedom-to-fail culture	1	0	0	0	0	0	0	2	0
15 : Internal champions ~ cross-functional squads	0	0	0	1	1	0	1	1	0
16 : Leadership mandate & budget control	0	1	2	1	0	5	0	1	1
17 : Middle-management role anxiety	0	1	0	0	0	1	1	0	0
18 : Skill & up-skilling programmes	1	0	2	0	0	0	0	1	1
29 : Technological Factors	4	3	12	1	2	5	3	6	5
19 : Cloud-ready infrastructure	1	1	5	0	0	0	0	0	0
20 : Data availability & quality	2	2	6	1	2	5	3	4	4
21 : Legacy-system integration	1	1	0	0	1	0	1	2	0
22 : On-prem vs. privacy-driven deployments	0	0	3	0	0	0	0	0	1
23 : Predictive maintenance (IoT)	1	0	0	0	0	0	0	0	0
24 : Vision ~ image-recognition use-cases	0	0	0	0	0	0	0	0	0

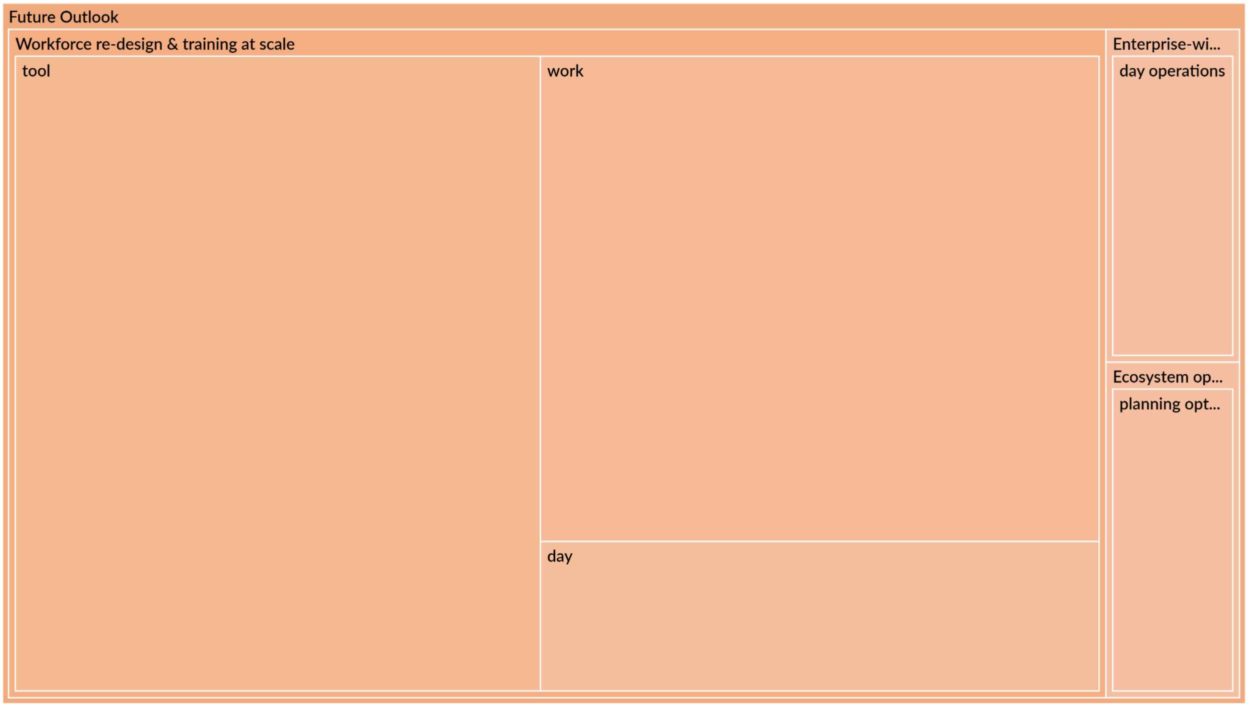
Appendix D: Showing the child factors mentioned the most during the interviewees for each parent






Organisational Factors
Leadership mandate & budget control
senior leadership team
management
leader...
senior leadership
current frame
channel level ...
leadership
business perspective
business decision
Skill & up-skilling programmes
data expert
separate...
real business us...
engineering team
Internal champions ~ cross-f...
team
Middle-management role anxiety
middle management
day-to ...
level
Freedom-to-fail culture
change management
skill change management


Motive for Adoption
Efficiency & cost-saving
time
process
store
right product
production pl...
supply chai...
pro...
pr...
inc...
fiel...
supply cha...
times schedule...
shelf ability...
data insights
con...
busi...
production pl...
third perspective
supply chain rule
profitabili...
daily sales ...
Data-driven insight ~ forecasting accuracy
planning
supply chain
invent...
data d...
current...
current...
supply syste...
perfect intel...
daily s...
sales trends
knowledge...
applica...
sales level ...
dealer mana...
Speed & scale in content ~ marketing
sales
marketing
main factor ...
content pr...
wh...
content b...
bra...
bra...
bra...
consumer...
complete p...
brand film
basically...
Competitive signalling ~ innovation branding
Risk & quali...



Appendix E: Interview Guide

Interview Guide

Introductory section:

1. Do you mind if we record this interview?
   Explain to participant that thesis is compliant with GDPR, company, name, ect.. will be anonymised with only their position within the organization and an assigned moniker used for identification
2. Can you briefly describe your role in the company and your main responsibilities?
3. How familiar are you with AI technologies in the FMCG industry (potentially explain FMCG)?
4. Has your company previously attempted to integrate AI into its business processes? If yes, in what areas?
5. How do you interact with AI within your work on a day to day basis?

AI Adoption and Decision Making Process

1. When was the initial decision to implement AI taken, and how long did the process of adoption and implementation take?
2. What were the main factors that influenced the decision to implement AI? (examples: cost savings, increased efficiency, competition)
3. Was there an internal advocate (change agent/s) for AI adoption?

Tech Factors

1. What types of AI technologies (if any) are currently used in your company? (e.g., predictive analytics, automation, marketing, inventory management)
2. How well do you think the company's existing IT infrastructure supports AI adoption?
    a. *(potential follow up)* What are the most essential pieces of IT infrastructure when it comes to supporting your AI systems?
3. What technological barriers if any do you face when trying to implement AI in operations? (e.g., lack of expertise, data quality issues, system integration problems)
4. How do you perceive AI's potential benefits for the company's supply chain, production, and distribution processes? -skip
5. How much did your existing access to data ease the transition to AI? (skip)
6. What type of data is stored with current systems?
    a. *(potential follow up)* How does its quality impact the efficacy of the AI systems?
7. To the best of your knowledge were the AI systemes built in-house, or did (the company) rely on third party vendors?

Organizational Factors:

1. How does senior leadership view AI adoption? Is it a strategic priority?
    a. (*potential follow up*): If so, what priorities are currently within scope when looking to adopt AI technologies
2. Do employees see AI as a helpful tool or a threat to their jobs? Why and in which ways?(follow up of which level is most resistant, mid level manager, execs, bottom level employees)
3. Have there been AI training or upskilling initiatives within the company? If not, what if anything would be required for successful AI integration?
4. In your experience, what is the main internal resistance (if any) to AI adoption among employees?
5. Was there support for the change from top management? **(skip)**
    a. How was this support expressed?
    b. What was the general outlook from employees on the change? Were there behaviours/perceptions influenced by support from management?
6. How did the company's financial position affect the decision to adopt and implement AI? **(skip)**

Environmental/Competitive Factors

1. How do competitors in the FMCG industry approach AI adoption?
2. How much did the competitive pressures influence the decision to adopt AI?
3. What role does customer preferences and demands play in the company's AI adoption decisions?
4. Are there any specific governmental actions/policies that have influenced your decision to adopt AI?
5. Have you encountered regulatory pain points which could slow down the overall adoption and implementation of AI within the FMCG market?

Challenges and Benefits

1. What were the expected benefits of AI pre-adoption?
    a. *(follow up)* What are the actual benefits and how do they compare to expectations?
2. What are key challenges the company faced while implementing AI?

Future Outlook:

1. What would be the key factors that could accelerate AI adoption in your company?
2. What are some best practices or success stories (if any) that you have observed regarding AI adoption within FMCG?
3. If you had unlimited resources, how would you implement AI to enhance business operations?
4. Do you believe AI will become a core component of the FMCG industry in India/Asia in the next five years? Why or why not?
5. Do you believe internal and external policy regarding AI and its adoption in business has caught up? Are there any current pain points with any of these policies?

Concluding

1. Is there anything else you would like to add that could help us understand AI adoption in your company or within the industry?