



**VILNIUS UNIVERSITY**  
BUSINESS SCHOOL

**DEEPTech ENTREPRENEURSHIP**

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**MASTER THESIS**

<b>KAIP DIRBTINIS INTELEKTAS FORMUOJA VERSLUMO STRATEGIJAS ŽAIDIMŲ PRAMONĖJE</b>	<b>HOW ARTIFICIAL INTELLIGENCE SHAPES ENTREPRENEURIAL STRATEGIES IN THE GAMING INDUSTRY</b>
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**Supervisor** \_\_\_\_\_

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Vilnius, 2025

## SUMMARY

VILNIUS UNIVERSITY BUSINESS SCHOOL

DEEPTECH ENTREPRENEURSHIP

Aliaksei Filonau

### HOW ARTIFICIAL INTELLIGENCE SHAPES ENTREPRENEURIAL STRATEGIES IN THE GAMING INDUSTRY

Supervisor - Lect. Jurgita Petrauskienė

Master's thesis (project) was prepared in Vilnius, in 2025

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The Master thesis examines how artificial intelligence (AI), including generative AI accelerated by the late-2022 “AI Spring,” reshapes entrepreneurial strategy in B2C game companies, using Electronic Arts (EA) as a single case. Literature discusses AI use in games and AI in entrepreneurship separately; integrated evidence on strategic reconfiguration in game studios is limited. The objective of the thesis is to develop a framework that systematises AI-driven entrepreneurial strategy. The tasks are to examine AI applications in the gaming industry, to identify its adoption challenges, to systematise strategic decisions that support AI adoption, and to integrate all insights and findings into a conceptual framework. The Master thesis research method is a qualitative single-case study of Electronic Arts based on public EA sources (reports/filings, earnings calls, press releases, interviews, keynotes, and R&D papers) from 2020-2025.

The Master thesis results demonstrate that AI applications in EA are unevenly distributed across the game lifecycle, namely concentrated in game creation and runtime/play, with fewer explicit AI uses in delivery. Benefits are named as efficiency, realism, and new experiences. Constraints include governance and legitimacy risks, infrastructure and skill requirements, and

AI-specific constraints. The Master thesis concludes that AI adoption follows strategic priorities. Strategic recognition and AI capability building accelerate feasible AI implementations. Recommendations include responsible AI governance, phased experimentation, and investment in data and skills.

The Master thesis results have not been published but can be adapted for publication.

## SANTRAUKA

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AUKŠTŲJŲ TECHNOLOGIJŲ VERSLAS

Aliaksei Filonau

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Magistro baigiamajame darbe nagrinėjama, kaip dirbtinis intelektas (DI), įskaitant generatyvųjį DI, kurio plėtrą paspartino 2022 m. pabaigoje prasidėjęs „DI pavasaris“, keičia verslumo strategiją B2C žaidimų įmonėse, remiantis vieno atvejo analize - „Electronic Arts“ (EA). Mokslinėje literatūroje DI taikymas žaidimuose ir DI verslumo kontekste dažniausiai aptariami atskirai, o integruotų įrodymų apie strateginį persitvarkymą žaidimų studijose yra nedaug. Darbo tikslas - sukurti sistemintą pagrindą, kuris susistemintų DI formuojamą verslumo strategiją. Darbo uždaviniai: išnagrinėti DI taikymo sritis žaidimų pramonėje, identifikuoti DI diegimo iššūkius, susisteminti strateginius sprendimus, kurie palaiko DI diegimą, ir integruoti įžvalgas bei rezultatus į konceptualųjį pagrindą. Tyrimo metodas - kokybinė vieno atvejo studija, paremta viešais EA šaltiniais (ataskaitomis ir oficialiais dokumentais, rezultatų skelbimo konferencinių skambučių medžiaga, pranešimais spaudoje, interviu, pranešimais renginiuose ir mokslinių tyrimų (R&D) publikacijomis) 2020-2025 m.

Magistro baigiamojo darbo rezultatai rodo, kad EA DI taikymai nevienodai pasiskirstę per žaidimo gyvavimo ciklą: jie labiausiai koncentruojasi žaidimo kūrimo ir vykdymo/žaidimo (runtime/play) etapuose, o pristatymo (delivery) etape aiškiai įvardytų DI taikymų yra mažiau. DI

nauda apibrėžiama kaip efektyvumas, didesnis realizmas ir naujų patirčių kūrimas. Apribojimais apima valdymo ir legitimumo rizikas, infrastruktūros ir kompetencijų reikalavimus bei DI specifinius ribotumus. Darbe daroma išvada, kad DI diegimas seka strateginiais prioritetais. Strateginis DI pripažinimas ir DI gebėjimų stiprinimas spartina įgyvendinamų DI sprendimų diegimą. Rekomendacijose pabrėžiami atsakingo DI valdymo principai, etapas eksperimentavimas ir investicijos į duomenis bei kompetencijas.

Magistro baigiamojo darbo rezultatai nebuvo publikuoti, tačiau gali būti pritaikyti publikavimui.

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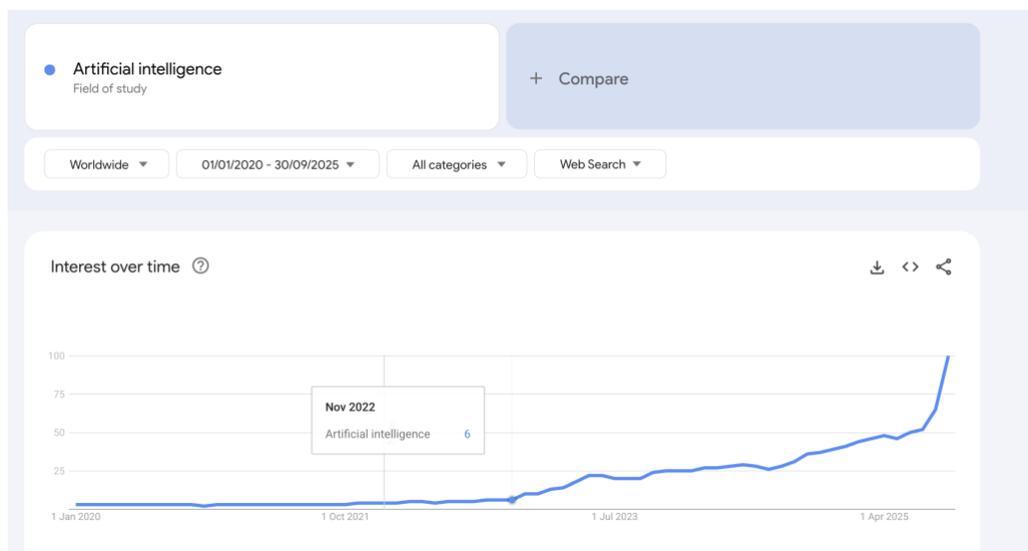
AFS	AI Feasibility Space
AI	Artificial Intelligence
AIS	AI Implementation Space
AISF	AI Strategy Framework
APS	AI Possibility Space
B2C	Business-to-Consumer
DDA	Dynamic Difficulty Adjustment
DRL	Deep Reinforcement Learning
EA	Electronic Arts
GAN	Generative Adversarial Network
GenAI	Generative Artificial Intelligence
IAP	In-App Purchase
IP	Intellectual Property
KPI	Key Performance Indicator
LLM	Large Language Model
NPC	Non-Player Character
OI	Open Innovation
PCG	Procedural Content Generation
QA	Quality Assurance
R&D	Research and Development
RDT	Resource Dependence Theory
RNN	Recurrent Neural Network
SME	Small and Medium-sized Enterprise
TAM	Technology Acceptance Model
TOE	Technology-Organisation-Environment framework
UTAUT	Unified Theory of Acceptance and Use of Technology
VAE	Variational Autoencoder
VGAI	Video Game Artificial Intelligence

## INTRODUCTION

Artificial intelligence has dominated the media space for the past several years. Although this technology has existed since roughly the mid-20th century (McCarthy et al., 2006), it has experienced various periods, from a decline called the "AI winter" (Crevier, 1993) to its current boom.

A particular boost in AI's popularity has arisen with the development of so-called generative AI; a key milestone in this process was the release of the ChatGPT chatbot, based on GPT models, on November 30, 2022 (OpenAI, 2022). Contrary to the earlier notion of an "AI winter," the current surge in artificial intelligence is often described as an "AI spring" (Bommasani, 2023). According to Google Trends (Google, 2025), global search interest in "Artificial Intelligence" has risen sharply (Figure 1) indicating substantial and growing public attention to the field.

**Figure 1.** Google Trends data on topic "Artificial Intelligence"



Source: Google (2025)

This growing interest has also prompted many businesses to explore how they might apply AI within their operations. As a result, AI has been adopted across a wide range of industries and has become an integral part of business processes.

Artificial intelligence is also attracting increasing attention from the scientific community. In the business studies, numerous papers have been written over the past years on the application of AI in various industries, including medicine (Chougule et al., 2025), finance (Bahoo et al., 2024),

banking (Godolja & Dom, 2024), agriculture (Taneja et al., 2023), and retail (Hassan & Hassan, 2025).

In the gaming industry, artificial intelligence has been used in one form or another almost since its inception. Since the dawn of video games, humans have competed against virtual opponents controlled by computer programs, beginning with early arcade games and simple non-playable characters or NPCs (Kuldeep Kundal, 2025; Spyscape, n.d.). In recent years, as this technology has developed and received increasing attention, artificial intelligence has found new uses within gaming companies. According to Google Cloud industry research and market analytics reports, for most gaming studios, the implementation of AI and efficiency tools is already part of a long-term development strategy and a source of new business models (AlixPartners, 2024; Google Cloud, 2025).

Within the gaming industry, research at the intersection of business and artificial intelligence focuses on the impact of AI on the development of the gaming industry and esports (Olkiewicz et al., 2025; Tran, 2025), the ethical aspects of using AI in games (Melhart et al., 2024), and other specific AI use case and applications.

In parallel, a distinct but only partially connected literature has begun to examine AI in the domain of entrepreneurship. A systematic review by Giuggioli and Pellegrini (2023) concludes that AI has “profound implications” for entrepreneurs but also notes a “lack of systematisation” and calls for an explicit research agenda on AI as an entrepreneurial enabler (Giuggioli et al., 2025). Uriarte et al. (2025) analyse 345 articles on AI technologies and entrepreneurship and find that, despite explosive growth in publications, most studies remain conceptually fragmented and “superficial”, prompting the authors to propose future research directions (Uriarte et al., 2025).

Herewith, there is no integrated study that studies how gaming studios reconfigures its entrepreneurial strategy in response to recent advances in AI, in particular generative AI and the “AI Spring” of late 2022 which was mentioned above. This gap is especially crucial given that leading industry players publicly describe AI as a core strategic priority and are beginning to position themselves as “AI first” companies (Peters, 2025).

This thesis intends to close this gap and examine how AI shapes entrepreneurial strategies in the gaming industry, with a particular focus on companies that develop and publish games directly for players (B2C). Understanding these dynamics is essential, as AI now influences not only in-game features but also production processes, business models, and strategic decision-making across the entire game lifecycle. Accordingly, the subject matter of this research intersects the domains of AI innovation, entrepreneurship, and strategic management within a gaming industry.

The **objective** of this thesis is to develop an analytical framework that systematises strategic approaches to AI adoption in B2C game companies and explains how AI shapes entrepreneurial strategies in the gaming industry.

To achieve this objective, the thesis addresses the following **tasks**:

- To examine the main applications of artificial intelligence in the gaming industry.
- To identify key challenges and constraints that limit the successful adoption of AI in game companies.
- To systematise strategic decisions that favour AI adoption.
- To integrate theoretical insights and empirical findings into a conceptual framework.

In line with the stated objective and research tasks, this thesis addresses the following **research questions**:

- RQ1: What practices of implementing AI can game companies use in their business strategies?
- RQ2: What challenges limit the successful adoption of AI in game companies?
- RQ3: What strategic decisions favour better AI adoption?

The thesis employs a qualitative single-case study approach, informed by Yin's case study methodology (2018) and operationalized through a structured case study protocol, using Electronic Arts as the case company. The methodological design integrates several data sources, including company reports, press releases, earning call, public interviews, keynotes and research papers. Data will be coded temporally (pre- vs. post-AI Spring 2022) and analysed through the lens of the AI Strategy Framework.

The thesis is structured into three main parts:

- Theoretical Part: Provides an overview of AI in the gaming industry, entrepreneurial strategy literature, and the conceptual framework.
- Methodological Part: Presents the research design, case selection logic, data collection, and analytical procedures.
- Research / Analytical Part: Reports case findings, analyses AI integration into strategy, identifies challenges and solutions, examines decision-making processes, and presents cross-case comparisons leading to strategic recommendations.

The concluding section synthesizes key insights, discusses implications, and outlines directions for further research.

The research is subject to several limitations arising both from the scope and from practical constraints encountered during the preparation of this work. These limitations do not invalidate

the findings, but they do affect the scope of the conclusions and the extent to which the results can be generalized beyond the studied context. Below, the key limitations are outlined.

The primary limitation is the use of a single case rather than a multiple-case study design, which limits the generalizability of the conclusions. Electronic Arts represents a very specific type of gaming company: a large, mature, publicly listed firm headquartered in the United States and operating at a global scale. Findings derived from this case may not be directly applicable to other gaming companies that differ in size (e.g., small or medium-sized studios), age (e.g., startups), geographic location (e.g., Europe or Asia), or organisational structure. While this limitation does not undermine the value of theory development within the case, it constrains the extent to which the results can be generalized across the gaming industry.

Another important limitation is that the analysis relies primarily on publicly available sources, such as company reports, earnings calls, interviews, and technical presentations. Public materials provide only limited access to internal decision-making processes. Companies selectively disclose information and may emphasize or downplay certain activities in public communications to protect confidentiality, manage public perception, or address investor expectations. As a result, publicly available data may not fully capture the internal dynamics of AI-related decision-making at Electronic Arts. This limits the level of precision with which internal practices and strategic processes can be described.

Finally, this research is based on qualitative rather than quantitative methods. While this approach allows for the identification and interpretation of patterns and relationships, it does not allow for precise measurement or statistical testing. Consequently, the findings should not be interpreted as statistically validated causal relationships, but rather as analytically grounded insights derived from qualitative evidence.

The author used AI tools, including generative AI, at several stages of the research process. These tools were employed to support idea generation, provide feedback on emerging concepts, correct grammatical and stylistic inconsistencies, and assist with data processing (as explained in detail in the methodological section). Importantly, the author does not treat AI as a substitute for the researcher or as a co-author, but rather as a contemporary analytical instrument that enables levels of productivity not previously accessible to earlier generations of scholars. It is somewhat paradoxical that research on AI could not be conducted without the aid of AI itself. However, this observation underscores the extent to which AI has become embedded in everyday academic and professional practices.

## **1. THEORETICAL FOUNDATION FOR AI IN THE GAMING INDUSTRY**

In this chapter, we establish the theoretical foundation for our study based on existing research papers and other literature sources, as well as conceptualize the theoretical model for our further research.

Section 1.1 reviews artificial intelligence in the context of the gaming industry. It defines artificial intelligence, outlines the categories of AI applications in the gaming industry, and discusses the benefits, risks, and implementation challenges associated with AI adoption in game companies.

Section 1.2 examines entrepreneurial strategies in innovation-driven contexts. It reviews relevant theoretical perspectives that explain how firms adopt and integrate new technologies under conditions of uncertainty, with particular attention to concepts of AI readiness, integration processes, and ecosystem-level strategies.

Finally, Section 1.3 synthesizes the reviewed sources into a conceptual framework. It introduces the AI Strategy Framework that guides the empirical analysis and forms the basis for the research.

### **1.1. Artificial Intelligence in the Gaming Industry**

In this section, we will review the role of AI in the gaming industry and establish key concepts for our thesis.

In Section 1.1.1, we will explore how AI can be defined in the gaming industry. We will identify a set of specific AI-related technologies that are applicable to game development and player experience.

Section 1.1.2. will provide an overview of the applications of AI within the gaming industry. We will see that AI can be applied in several ways. Firstly, it can be integrated as a component of the game, for example, for NPC behaviour and dynamic difficulty adjustment (DDA). Secondly, AI can be used for game production and operation, being used for game testing, asset creation, and other related purposes.

Finally, Section 1.1.3. will analyse challenges and risks associated with implementing AI-related technologies within gaming companies. It will include technological challenges (computational demands, data scarcity, and the complexity of integrating AI systems) and ethical challenges (biases of AI algorithms, job replacement, and data protection).

### 1.1.1. Definitions of AI in the context of the game industry

Since the early days, video game developers have relied on scripted algorithms to animate non-player characters (NPCs) and make them feel alive (Sun 2025; Yi 2024). These algorithms are still referred to today by gamers and developers as "artificial intelligence", which raises the question of what constitutes artificial intelligence in the context of the video game industry.

The literature offers several, sometimes conflicting, ways to understand what "artificial intelligence" (AI) means in the context of games. A constant theme is the historical separation between "academic" AI and the AI that game studios deploy (Pfau et al., 2020; Mattei, 2024). Scholars typically define AI as machines or algorithms that solve general perception or other problems on the same level as a human, whereas game studios have long preferred purpose-built techniques whose main goal is to appear intelligent and maximize player enjoyment (Geng, 2023). Mattei (2024, p. 41) notes that video-game AI (VGAI) "does not respect the ... academic sense, but this fact is perfectly fine, as the main purpose of VGAI is to be believable." They implicitly accept the notion of "weak" or task-specific AI - for example, systems optimized for controlling NPCs - rather than "strong" human-level intelligence (Bory et al., 2025). We can therefore conclude that AI in gaming is task-specific rather than universal. Below, we proceed with the determination of key clusters in the definition of AI for the gaming industry.

A first cluster of definitions stresses AI's entertainment function. For Geng (2023, p. 671), "the fundamental objective of AI is to increase the entertainment of games but not make more trouble to players." Jiang et al. (2024, p. 422) similarly frames AI as "intelligent algorithms to create responsive, adaptive, and challenging gameplay experiences," while Tian (2024, p. 161) emphasizes vividness and motivation. These perspectives focus on in-game behaviour and see AI primarily as a tool for immersion and players' fun.

A second cluster, exemplified by Zhao et al. (2020, p. 199), uses the term "game-playing AI" to describe any agent (rule-based or deep-RL) that simulates a player. This definition deliberately brackets the technology and centres on the function: controlling an entity that can compete with humans inside the game world.

Pfau et al. (2020) report that only a small minority of shipped games exploit recent academic breakthroughs. To mitigate possible risks, game studios tend to use simpler, deterministic approaches. Shaikh (2025) states that non-adaptive methods are more popular among game developers. Risi & Preuss (2020) observe that for many years, researchers and developers "were largely unconnected," so academic progress did not translate into production

pipelines. In practice, therefore, commercial games mostly rely on hand-authored algorithms that give studios tight, predictable control over their games.

But this is not the case if we expand our view to AI beyond the game itself. While most of the mentioned approaches confine AI to the in-game experience only, the third cluster of definitions considers AI throughout the entire entertainment product lifecycle (Anantrasirichai & Bull, 2022; Hu et al., 2023). Hu et al. (2023) describe the various types of AI for specific processes inside a game company: game development, game experience, and game operation. We will review these use cases in detail in section 1.1.2.

Taken together, the literature presents three ways to think about AI in the gaming industry:

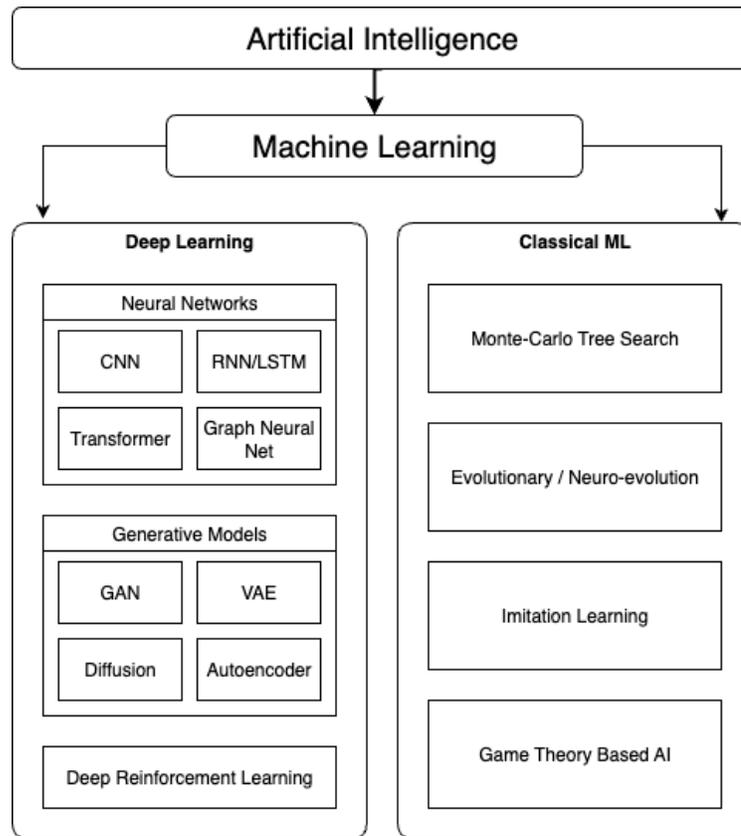
- Entertainment / Believability lens - AI is any technique that creates the illusion of intelligence to serve entertainment (Geng, 2023; Mattei, 2024).
- Gameplay-function lens - AI comprises algorithms that make NPCs and game systems responsive, adaptive, and challenging, effectively simulating a human player (Zhao et al., 2020; Geng, 2023; Jiang et al., 2024).
- Product-lifecycle lens - AI encompasses all AI-labelled technologies used anywhere in the game lifecycle, from prototyping to post-launch operations (Anantrasirichai & Bull 2022; Hu et al. 2023)

For the purposes of this thesis, the third perspective is the most useful. We are interested not only in how AI shapes what the player sees on-screen, but also in how AI technologies influence entrepreneurial decision-making and capabilities across the entire studio's value chain. Consequently, we define AI in this study as:

*A set of AI-labelled technologies that can be applied to enhance the efficiency of any stage of the game lifecycle.*

From this definition, we have developed a schematic overview that categorizes AI-labelled technologies relevant to the gaming industry (**Figure 2**).

**Figure 2.** AI-labelled Technologies



*Source:* Compiled by the author on the basis of Anantrasirichai & Bull (2022); Hu et al. (2023)

### 1.1.2. Overview of AI Applications in the gaming industry

Building on the definition of AI, this subsection summarizes the concrete ways in which AI can be used in the game lifecycle. Our taxonomy (**Table 1**) is based on two recent state-of-the-art surveys that systematise the field: Anantrasirichai and Bull's review of AI in creative industries (2022) and Hu et al.'s deep-learning survey in games (2023).

**Table 1. Applications of AI in the gaming industry**

Stage	AI Cluster	Use Cases	Technology families
Game Creation	Idea generation and prototyping	Generate ideas for story, game mechanics, concept art and mood-board images, rapid balance simulations	Transformer, Diffusion, Deep Reinforcement Learning, Evolutionary / Neuro-evolution
Game Creation	Asset creation	Generate art, audio (music/voice), animation, 3D models, and texts for usage in the game	Diffusion, GAN, VAE, Autoencoder, Transformer
Game Creation	Coding	Make gameplay scripts, suggest refactors and performance fixes	Transformer
Game Creation	Testing and QA	Test game levels, generate regression suites, stress-test server loads (for online), visual glitch detection, emotion-aware playtesting	Deep Reinforcement Learning, Imitation Learning, Evolutionary / Neuro-evolution, CNN, Vision Transformers
Game Creation	Localization	Instant text/audio localization, cultural-sensitivity analysis of assets, auto voice-over dubbing	Transformer
Game Delivery	Marketing	Generation of marketing materials, segment audiences,	Diffusion, Transformer, CNN

---

Stage	AI Cluster	Use Cases	Technology families
		optimise bidding & spend	
Game Delivery	Player analytics and modelling	Churn/lifetime value prediction, persona discovery, session-length forecasts, personalised IAP prices, adaptive bundles, promotion timing	RNN/LSTM, Graph Neural Net, Deep Reinforcement Learning
Game Delivery	Community-management	Toxicity/hate-speech filters, reputation scoring, moderator-queue triage	Transformer, Graph Neural Net
Game Delivery	Customer support and Feedback analysis	FAQ self-service, mine reviews and social posts for sentiment and feature requests	Transformer
Game Delivery	Fraud detection	Detect bots/aim-hacks, flag RMT networks, catch payment fraud	Graph Neural Net, CNN, RNN/LSTM
Game Delivery	Live-ops optimization	Schedule events, guide A/B roll-outs, personalise content pushes	Deep Reinforcement Learning
Play / Runtime	Non-playable characters (NPC)	Lifelike dialogue, pathfinding, adaptive tactics,	Transformer, Deep Reinforcement Learning

---

Stage	AI Cluster	Use Cases	Technology families
		lore-consistent responses	
Play / Runtime	Dynamic difficulty adjustment (DDA)	Real-time tuning of enemy skill, puzzle complexity, spawn rates	Deep Reinforcement Learning, supervised regression, Tree Search (Yin et al., 2023)
Play / Runtime	Procedural generation (PCG)	On-the-fly levels, quests, tailored to player state	VAE, Diffusion, GAN, Transformer
Play / Runtime	Real-time enhancement	visual Neural up-scaling, super-resolution, frame interpolation	CNN, GAN, Autoencoder
Play / Runtime	Match-making	Fair team formation, rank updates, party-cohesion balancing	Graph Neural Net

*Source:* Compiled by the author on the basis of Anantrasirichai & Bull (2022); Hu et al. (2023)

It is important to note that our taxonomy is not an overview of actual industry deployment because commercial studios rarely disclose the algorithms that power their pipelines due to confidentiality and intellectual property reasons (Pfau et al., 2020). However, while the real-world adoption level of each use-case remains uncertain, we can be confident that at least some of the mentioned AI-technologies have already been implemented in practice by certain game companies, for example usage of CNNs in King (Candy Crash Saga) for estimation of difficulty of new game levels (Gudmundsson et al., 2018).

#### (a) Game Creation

Scholars widely frame the early stages of development as the point where generative AI could deliver its greatest leverage, describing gaming as “a very clear case study” for GenAI

across an entire value chain (Gozalo-Brizuela & Garrido-Merchán, 2023, p. 16). Research on AI-assisted game design shows language models proposing story beats, design-document sections and even first-pass rule sets. Cook (2022) presents Puck, an automated designer embedded in local creative teams, while JaeJun Lee et al. (2023) observe how AI tools shift roles during the concept-pitch phase. In an expert study, Lankes and Stöckl (2023) found that ChatGPT could help professionals with idea generation, documentation drafts and early exploration of game-mechanic variants.

Generative pipelines extend from text to content. Moon et al. (2025) note that large environments can be procedurally produced instead of hand-crafted. Merino et al. (2024) demonstrate that GPT-4, with domain-specific prompting, can compose word-puzzle sets competitive with human creations. Gallotta et al. (2024) introduce *LLMaker*, which lets designers co-author game content with an LLM. Asset research is equally active. Pose-estimation networks turn video footage into 3-D animations (Xian & Sahagun, 2023). Begemann and Hutson (2024) outline an end-to-end 3-D-model pipeline that connects generative models to Unreal Engine's Nanite optimization; and diffusion models contribute both textures and concept art (Gozalo-Brizuela & Garrido-Merchán, 2023). Audio creation, too, is singled out as an area where AI-tools could raise quality and reduce workload (Yang & Nazir, 2022).

Quality-assurance literature is growing fast. DRL or imitation-learning agents now explore unseen levels and estimate difficulty far faster than human testers (Gudmundsson et al., 2018). Behaviour-cloned bots trained on gameplay video achieve 89.5 % "human-likeness", outperforming earlier baselines (Leninsengathir et al., 2025). CNN-based glitch detectors, facial-expression analysis for frustration spotting, and new search-based test agents are all under active investigation (Kwon et al., 2022; Yi, 2024; Shirzadehhajimahmood et al., 2025). Finally, localization research has moved from neural MT to pipelines that score cultural fit in feedback and assets (Jiang, Jia & Hu, 2024).

#### (b) Game Delivery - marketing, live-ops and infrastructure

Once content-complete, a game must reach and retain players. Player-modelling work begun in mobile free-to-play shows how behavioural profiles could let marketing campaigns tailor creative, pricing or IAP bundles in real time (Mattei, 2024; Hu et al., 2023). AutoML tabular models optimise spend, while diffusion tools accelerate asset production of advertisement assets. Community-health and security studies apply graph and deep-learning methods to detect abnormal player behaviour or control-input patterns (Ravikanth Konda, 2022; Pinto et al., 2021) and to classify toxicity clusters or bot networks (Fang, 2022).

Some authors envisage in-client virtual assistants that personalise on-boarding and support (Kandur, 2025).

Technical operations are another research focus. CNN-powered super-resolution (DLSS, FSR) lets studios deliver high-fidelity visuals without raising minimum hardware specs, while reinforcement-learning profilers could tune graphics, framerate and memory budgets per device (Wang, 2024; Sun, 2025). Similar agents have been proposed for cloud-gaming stacks, where they would route traffic, adjust codecs and allocate servers to preserve latency (Naveen, 2024). Whether such systems are widely deployed remains undocumented.

### (c) Play / Runtime - real-time personalisation

During live play, AI research concentrates on immersion and fairness. Transformers, behaviour trees and deep or multi-agent reinforcement learning are combined to drive natural-language dialogue, navigation and tactics for non-player characters. Studies on improvement of NPCs behaviour with the use of AI technologies is still a popular area for researchers (Alonso et al., 2021; Nash et al., 2023; Shaikh, 2025; Uludağlı & Oğuz, 2023). Quality of NPCs has a direct impact on the game quality: personality, emotional intelligence and social presence correlate with player satisfaction and sequel intent (Markus et al., 2024).

Adaptive-challenge systems modulate puzzles or combat to keep players in the flow zone, using contextual bandits, supervised models or DRL (Jiang et al., 2024; Mortazavi et al., 2024). Even the long-standing domain of path-finding - essential for avoiding erratic navigation - continues to evolve, blending A\* with learned heuristics (Pfau et al., 2020).

Procedural content generation spans text-to-level pipelines and GAN-based adaptive music, enabling on-the-fly quests, world-building vegetation or reactive soundtracks (Silva et al., 2025; Merino et al., 2024; Dorsey et al., 2023; Pfau et al., 2020). Graph-based matchmaking maintains competitive balance (Hu et al., 2023), while deep learning and convolutional neural networks are applied to enhance lighting, rendering, camera systems, and post-processing effects in video games (Wu et al., 2023). Survey work foresees highly personalised games with human-like opponents and fluid narratives emerging as AI techniques mature (Tian, 2024).

### 1.1.3. Benefits of AI in the Gaming Industry

The most obvious benefit of AI for gaming is the improvement of team's production efficiency and creativity. By automating the generation of levels, textures, or even whole environments, PCG "speed[s] up the generation of game assets" and frees artists to "focus more

on the artistic and design side of the product” (Mattei, 2024, p. 50). The payoff is twofold: shorter production schedules and higher job satisfaction, because repetitive, low-value tasks are replaced with higher-level creative problem-solving.

Beyond pure asset creation, recent generative-AI workflows let designers prototype ideas directly. The possibility to sketch a prompt in natural language and to see an in-engine scene seconds later reduces the costly “translation gap” between concept and implementation. According to JaeJun Lee et al. (2023, p. 229), the “most significant difference for game designers is the ability to visualise their creative thoughts without losing them in communication,” substantially cutting iteration cycles. These productivity gains carry strategic weight: teams can experiment with more design variants, pursue bolder artistic directions, and reallocate resources from content production to activities that differentiate the final product (e.g., fine-tuning core mechanics, polishing narrative arcs).

Player satisfaction increasingly hinges on games that feel responsive to individual preferences and skill levels. AI techniques enable real-time personalisation across multiple dimensions. By mining live telemetry, developers can “understand player behaviour, shape narratives, and tailor challenges in real time” (Madre et al., 2024, p. 1476). DDA systems, for example, have been shown to “feel more fun for players and increase engagement” (Mortazavi et al., 2024). Intelligent narrative engines produce branching stories and mission structures that stay coherent while evolving to match emergent play styles, helping players perceive the world as alive and reactive (Zhang, 2024). AI-driven behaviour models “provide more realistic and challenging opponents,” raising tension and immersion (Lin, 2024, p. 191).

Empirical evidence supports the engagement boost: Lin’s (2024) study links AI-generated environments, NPCs, and storylines with significantly higher player involvement metrics, while an exploratory survey found that 83 % of respondents believe AI increases game realism and 45 % actively seek AI-powered dynamic content.

One of PCG’s classic appeals is “increasing replayability by offering the player a new experience every time they play” (Risi & Preuss, 2020, p. 11). When procedural systems are coupled with AI-driven player modelling, each game session can present genuinely novel layouts, quests, or puzzles that still respect a player’s evolving competence. It extends a title’s lifecycle and strengthens community retention.

Generative models that create or remix content on-the-fly (collectively referred to as AI-generated content, AIGC) amplify this effect. Wang and Hu (2024, p. 129) demonstrate that AIGC “significantly increases user engagement by creating personalised, immersive experiences” and in turn “pave[s] the way for future innovation and prosperity in the gaming industry.”

Reaching global audiences demands nuanced localization that goes beyond literal text translation. Jiang et al. (2024) employ a multi-layer neural network combining convolutional and recurrent layers to mine cultural cues in both game assets and player feedback. Their findings show a “strong correlation between AI-guided cultural adaptation and market success,” as culturally attuned content generates measurably higher engagement compared with traditional localization workflows. For entrepreneurial studios, such automated cultural analytics lower the barrier to entering new regions while mitigating the reputational risks of insensitive content.

Collectively, the evidence positions AI not merely as a cost-saving tool but as a strategic lever that simultaneously compresses production timelines, enriches the moment-to-moment player journey, enhances innovation capabilities (Gao et al., 2025) and unlocks new markets (Tominc et al., 2023). These benefits map directly onto the entrepreneurial imperatives of game studios - speed to market, product-market fit, and revenue scalability.

#### **1.1.4. Risks of AI in the Gaming Industry**

Academic and industrial discourse now widely recognises the transformative potential of artificial intelligence (AI) for game development, yet the incorporation of contemporary AI techniques into commercial pipelines remains fragmented and cautious. In interviews with industry practitioners, Pfau, Smeddinck, and Malaka (2020) found broad enthusiasm for academic advancements, but equally strong reservations about their immediate production value. This ambivalence stems from a dense constellation of technical, organisational, and ethical factors that collectively shape adoption decisions.

A primary risk is the sheer computational intensity of state-of-the-art models. Reinforcement-learning agents, generative adversarial networks (GANs), and foundation models often require hardware budgets well beyond what most studios (or their target platforms) can sustain. Yin et al. (2023) observe that training competitive agents typically demands extensive clusters or cloud time, while Zhao et al. (2020) show that every new game or level variant forces a proportional increase in engineering effort and inference cost. Even where cloud offloading is feasible, optimization for mobile or legacy hardware remains a research priority (Chergarova et al., 2024).

Equally challenging is the limited generalisability of current algorithms. Techniques that achieve human-level performance in Chess, StarCraft II, or narrowly defined benchmark environments fail to transfer “out of the box” to new rule systems, mechanics, or even alternate

maps (Risi & Preuss, 2020; Yin et al., 2023). Re-tuning or re-training becomes mandatory whenever designers iterate on core gameplay, thereby undermining one of the supposed efficiencies of AI-driven tooling. This brittleness also complicates automated playtesting: Hu et al. (2023) and Wang (2023) each highlight how rapidly evolving rulesets outpace an agent's training data, forcing constant retraining cycles that strain production schedules.

The day-to-day usability of AI tools further limits uptake. Most open-source frameworks presuppose machine-learning expertise that level designers, gameplay programmers, and artists rarely possess. In general, lack of employees' technical skills and AI literacy constitutes a major challenge for AI implementation (Tominc et al., 2023; Ersanlı et al., 2025).

Participants in both Pfau et al.'s (2020) study and Justesen, Bontrager, Togelius, and Risi's (2020) survey stressed that an algorithm must be transparent, easily debuggable, and expose designer-friendly knobs; otherwise, it is simply too risky to embed in milestone-driven production. Boucher, Smith, and Telliel (2023) add that even generative AI interfaces pitched at non-experts often fail to supply game-ready or stylistically coherent assets, compelling artists to revert to traditional workflows.

Resource considerations dovetail with the above technical issues. Beyond hardware, AI initiatives require large, well-curated datasets, specialised engineering support, and extended quality-assurance passes. Studios therefore incur "considerable labour effort" in implementation, adjustment, and regression testing (Pfau et al., 2020). Smaller companies are particularly exposed: Shaikh (2025) and Gomez-Alvarez et al. (2024) note that experimentation costs and uncertain return on investment deter many independent teams from anything more than exploratory prototypes.

Behavioural robustness introduces another layer of uncertainty. When non-player characters (NPCs) derive decisions from high-variance neural policies, they may oscillate between uncanny competence and immersion-breaking incoherence. Amanyurag and Sudheer (2025) underline persistent problems with erratic or repetitive behaviours, while Shaikh (2025) documents player frustration when AI "cheats" by exploiting states invisible to humans. Designers must therefore balance technical sophistication against the experiential imperative for believable, learnable opponents.

Overlaying these implementation challenges is a broad suite of ethical, social, and legal risks. Bias embedded in training corpora can manifest as discriminatory NPC reactions or unequal matchmaking outcomes, undermining a studio's inclusion goals (Madre et al., 2024; Wu et al., 2023). Players increasingly demand transparency about how adaptive systems collect and process their data, a concern that intensifies when AI clones a user's likeness for in-game

characters (Zhai, 2024) or leverages personal telemetry for monetisation loops (Jiang, 2024). Sun's (2025) survey of players found privacy anxieties to be the single most cited worry, eclipsing even fears of job displacement.

Labour dynamics reinforce those anxieties within development teams themselves. Generative pipelines threaten to deskill certain roles while amplifying demand for AI specialists, creating pockets of resistance rooted in both job security and professional identity. Alharthi's (2025) qualitative study highlights widespread unease about originality and authorship; Johansen and Mourath (2024) report that younger developers, in particular, decline to use generative systems on ethical grounds or because the outputs lack creative specificity. Paradoxically, mature developers (which often are more fluent in custom tooling) express greater enthusiasm, suggesting a generational skills gap that organisations must bridge through targeted training and governance.

Legal uncertainty compounds ethical risk. The provenance of data used to train large generative models is rarely transparent; consequently, assets produced with such models may violate third-party copyrights (Begemann & Hutson, 2025). Until jurisprudence clarifies authorship and fair-use boundaries, studios mitigate exposure by limiting generative assets to prototypes or placeholders, a practice corroborated by Johansen and Mourath's (2024) industry survey.

Finally, integrating AI widens the surface area for adversarial attacks. Players frequently perceive AI-controlled agents and automated behaviours as undermining fair play and competitive integrity, particularly when such systems resemble cheating or scripted play (Wu, 2023). Robust security and auditing processes thus become non-negotiable components of an AI deployment strategy, adding yet another cost centre to an already expensive endeavour.

In sum, the pathway to AI adoption may be obstructed by technical barriers, substantial development costs, and a complex set of ethical, legal, and social risks.

## **1.2. Entrepreneurial Strategies in Innovation-Driven Context**

In this section, we will review the strategies for the implementation of AI in the gaming companies.

In section 1.2.1. we will introduce the concept of AI readiness and investigate how current research defines the conditions required for successful AI implementation. For this purpose, we will review Technology-Organisation-Environment (TOE) framework and Dynamic Capabilities theory.

Section 1.2.2. will guide us through the process for AI implementation by reviewing such methodologies as Agile, Lean Startup and introducing relevant business theories and frameworks, including Resource orchestration theory and Unified Theory of Acceptance and Use of Technology (UTAUT).

Finally, Section 1.2.3. will give us the view to AI implementation through the concepts of ecosystem and partnerships. In particular, we pay our attention to the recent development of open innovation (OI) and resource dependency theory (RDT).

### 1.2.1. Readiness of the Firm

Readiness is often treated as the first condition for AI adoption. A firm that lacks basic infrastructure, managerial support, or an enabling environment will find it difficult to integrate AI into its workflows, no matter how promising the technology. The TOE framework provides one of the most widely cited lenses for analysing readiness. It emphasizes that adoption depends on three interacting dimensions: technological context, organisational context, and environmental context (Baker, 2011; Enholm et al., 2022). While TOE is not AI-specific, it has been adapted in numerous studies of AI adoption, showing its flexibility across industries.

**Technological readiness** encompasses IT infrastructure, software compatibility, and data availability. In gaming, technological barriers can be decisive, as AI models are computationally intensive and require integration into complex development pipelines. Chergarova et al. (2024) highlight the importance of ensuring hardware and software compatibility when embedding AI into engines like Unity or Unreal. Similarly, Ali and Khan (2025) identify IT infrastructure, compatibility, and resource availability as universal adoption factors across industries. Weber et al. (2022) expand on this point by identifying data management and AI model lifecycle management as critical organisational capabilities that mitigate AI's dependence on high-quality, constantly updated datasets.

In practice, this means that studios lacking robust pipelines risk brittle AI models that require repeated retraining whenever design parameters shift. Uren and Edwards (2023) propose extending readiness frameworks with explicit **data readiness** criteria, given that AI models cannot perform without reliable data. This addition is particularly relevant to gaming companies, where telemetry data, user interactions, and QA outputs serve as inputs to machine-learning systems. A firm that has not invested in accessible, well-structured datasets may find itself excluded from AI opportunities despite possessing otherwise adequate infrastructure.

Beyond infrastructure, **organisational readiness** determines whether firms can strategically mobilize AI. Leadership commitment is consistently cited as a decisive factor. Jöhnk et al. (2021) identify top management support as one of the most critical AI-specific readiness factors, while Ali and Khan (2025) highlight resource availability and cultural readiness. From the perspective of upper echelons theory, organisational strategy reflects the cognitive orientation of top managers. Pinski et al. (2024) argue that **AI literacy across the top management team** is necessary: if only one executive is knowledgeable about AI, the topic risks being marginalized or siloed. Conversely, when executives collectively understand AI's potential and risks, adoption strategies receive sustained attention and resources.

Organisational culture also plays a central role. Ambidextrous cultures that balance efficiency and exploration have been shown to enhance innovation capacity (Muhammad et al., 2021). In gaming studios, this ambidexterity may mean using AI to automate repetitive asset production while simultaneously experimenting with generative design tools to push creative boundaries. Workforce readiness is equally important. Studies emphasize the dual necessity of technical skills (machine learning, programming, data analysis) and soft skills (adaptability, creativity, ethical reasoning) (Morandini et al., 2023; Babashahi et al., 2024). Fenwick et al. (2024) stress that human resource management must actively support AI adoption by promoting human-centric strategies, ensuring that AI enhances rather than undermines employees' roles.

**Environmental readiness** captures external factors such as regulation, vendor support, and competitive pressure. Sánchez et al. (2025) show that in small and medium-sized enterprises (SMEs), vendor and partner support, alongside regulatory frameworks, strongly influence adoption decisions. Khanfar et al. (2025) similarly highlight environmental factors such as industry regulations and partner ecosystems as significant adoption determinants. In gaming, dependencies on third-party engines, cloud providers, and middleware vendors make environmental readiness especially salient. Arroyabe et al. (2024), however, caution that internal digital and innovation capabilities often outweigh environmental support, suggesting that firms cannot rely solely on favourable external conditions.

While TOE and related frameworks treat readiness as a relatively static condition (snapshot of conditions), certain studies advocate for a **dynamic capabilities** perspective. Dynamic capabilities describe how firms continuously sense opportunities, seize them through investments, and transform their structures to adapt to changing environments (Teece et al., 1997). Arroyabe et al. (2024) apply this lens to SMEs adopting AI, showing that digital and innovation capabilities jointly determine adoption outcomes. Gao et al. (2025) provide empirical evidence of a positive correlation between AI adoption and innovation capability, reinforcing the

argument that readiness is not fixed but evolves over time. For gaming firms, this implies that adoption cannot be a one-off decision but must be part of a broader entrepreneurial capability to reconfigure processes as AI technologies and player expectations change.

### 1.2.2. Processes for AI Integration

Once firms achieve a degree of readiness, they must decide how to actually integrate AI into their workflows. The literature consistently shows that AI adoption differs from conventional IT implementation: it is more experimental, iterative, and uncertain, requiring firms to balance flexibility with control. Entrepreneurial strategies for integration therefore emphasize agility, phased scaling, governance, and resource orchestration.

**Agile methodologies** have been widely recommended for AI integration. Tominc et al. (2023) highlight flexibility, continuous learning, and collaboration as key enablers of AI implementation. Haefner et al. (2023) observe that machine-learning practitioners often work in sprints, iteratively refining models. In the gaming industry, agile practices enable teams to prototype generative systems, test them with limited player groups, and refine outputs without committing to large-scale deployment. Chergarova et al. (2024) also note that agile practices facilitate collaboration between AI specialists and creative designers, ensuring that technical solutions align with artistic goals.

An approach closely related to agile is the **Lean Startup (LS) methodology**, which emphasizes iterative experimentation and validated learning. Bortolini et al. (2018) note that LS treats organisational learning as both a strategic objective and an operational tool, supporting not only product design but also broader business-model validation. Recent empirical work confirms its relevance for AI adoption: Wang and Wu (2025) show that firms combining AI with LS achieve faster development cycles, higher-quality products, and broader innovation outcomes, while AI adoption without LS yields limited gains. For game studios, LS provides a framework for testing AI-driven features in small-scale experiments, collecting feedback, and adapting both product and business-model assumptions. This complementarity suggests that AI delivers its greatest entrepreneurial benefits when embedded within structured learning processes.

(b) Phased adoption. Haefner et al. (2023) propose a three-phase model of AI adoption: proof-of-concept, productionisation, and platformisation. Each stage involves both technical and social components. Proof-of-concept projects often rely on simple models and external services, helping firms test feasibility. Productionisation requires robust infrastructure and compliance

mechanisms, while platformisation democratizes AI access across the organisation. In gaming, this progression might involve starting with AI-based QA testing, moving to AI-assisted level design, and eventually creating internal AI platforms accessible to multiple teams. Frenkenberg and Hochman (2025) add that phased adoption reduces employee anxiety: moderate exposure builds familiarity, while excessive reliance increases concerns over dependency and loss of control.

**Resource orchestration theory** complements process perspectives by explaining how firms actively manage resources. Peretz-Andersson et al. (2024) identify three stages: structuring AI resources (assembling technological, human, and procedural assets), bundling them into capabilities, and leveraging them for competitive advantage. For gaming firms, orchestration might involve combining AI asset generation tools with data analytics platforms and embedding them into a coherent production pipeline. This dynamic process highlights that integration is not just about adopting tools but about strategically coordinating resources across the organisation.

(d) Governance and responsible integration. Governance is another central element of integration. Papagiannidis et al. (2025) outline principles of responsible AI accountability, transparency, fairness, human oversight, and privacy. All of them must be embedded into adoption processes. Rana et al. (2022) warn that without governance, AI adoption risks operational inefficiencies, such as poor data quality or ineffective training. In gaming, responsible AI governance is critical not only for internal efficiency but also for maintaining player trust, particularly in areas such as personalisation and monetisation.

### 1.2.3. Individual strategies and Ecosystem Strategies

The final perspective emphasizes that AI adoption in gaming succeeds only if individuals and ecosystem is taken into account in the process of adoption. The process of AI adoption therefore must take into account individual adoption and ecosystem leverages.

The **Unified Theory of Acceptance and Use of Technology (UTAUT)** identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of user adoption (Venkatesh et al., 2003). Menon and Shilpa (2023) extend UTAUT to AI contexts, finding that perceived interactivity and privacy concerns influence user engagement with ChatGPT. Complementary theories such as the **Technology Acceptance Model (TAM)** and **Diffusion of Innovations (DOI)** emphasize perceived usefulness, ease of use, and innovation characteristics (Radhakrishnan & Chattopadhyay, 2020; Khanfar et al., 2024).

These frameworks suggest that in gaming studios, designers' and developers' willingness to trust and use AI systems is as critical as managerial decisions to adopt them.

AI reshapes **open innovation (OI)** by enabling hybrid models of human-AI collaboration. Holgersson et al. (2024) argue that AI can enhance, enable, or replace certain OI practices, while the most promising future lies in hybrid models that combine AI-driven ideation with human contextualization and ethical judgment. Meireles et al. (2022) highlight the importance of inter- and extra-organisational collaboration, which is often underexplored in innovation studies. For game studios, OI may involve partnerships with AI research labs, participation in open-source projects, or engagement with player and modding communities.

According to **resource dependency theory (RDT)**, firms rely on external resources for survival but must manage dependencies to avoid excessive reliance (Arroyabe et al., 2024). In gaming, dependence on third-party engines, middleware vendors, and cloud providers is widespread. Khanfar et al. (2025) and Sánchez et al. (2025) show that vendor support, regulatory context, and competitive pressure strongly influence adoption. Pushpakumara and Jameel Ahsan (2025) recommend strategies such as leveraging cloud-based solutions for infrastructure gaps and investing in training programs to overcome organisational resistance.

In summary, entrepreneurial strategies for AI adoption in the gaming industry span three interconnected layers. **Readiness of the firm** establishes the necessary technological, organisational, and environmental conditions, enhanced by dynamic capabilities. **Processes for integration** involve agile experimentation, phased scaling, governance, and the orchestration of resources. Adoption of AI is also complemented by adoption theories that explain **individual acceptance**. **Ecosystem strategies** extend the firm's boundaries, highlighting the role of open innovation, dependency management, and business-model evolution. Together, these perspectives prepare the ground for Section 1.3, where we synthesize them into a conceptual framework tailored to B2C game studios navigating the uncertainties of AI adoption.

### 1.3. Conceptual framework of AI Strategy in the Gaming Industry

In this section, we summarize our findings and set a theoretical basis for our further research

Section 1.3.1. synthesizes our findings in the AI Strategy Framework. For this purpose, we adopt the product-lifecycle view of AI use cases (game creation, game delivery and play), AI benefits and risks from section 1.1. and the concepts of AI readiness, processes of AI integration and ecosystem strategies for AI from section 1.2.

In section 1.3.2. we make hypotheses for our research questions based on our conceptual framework.

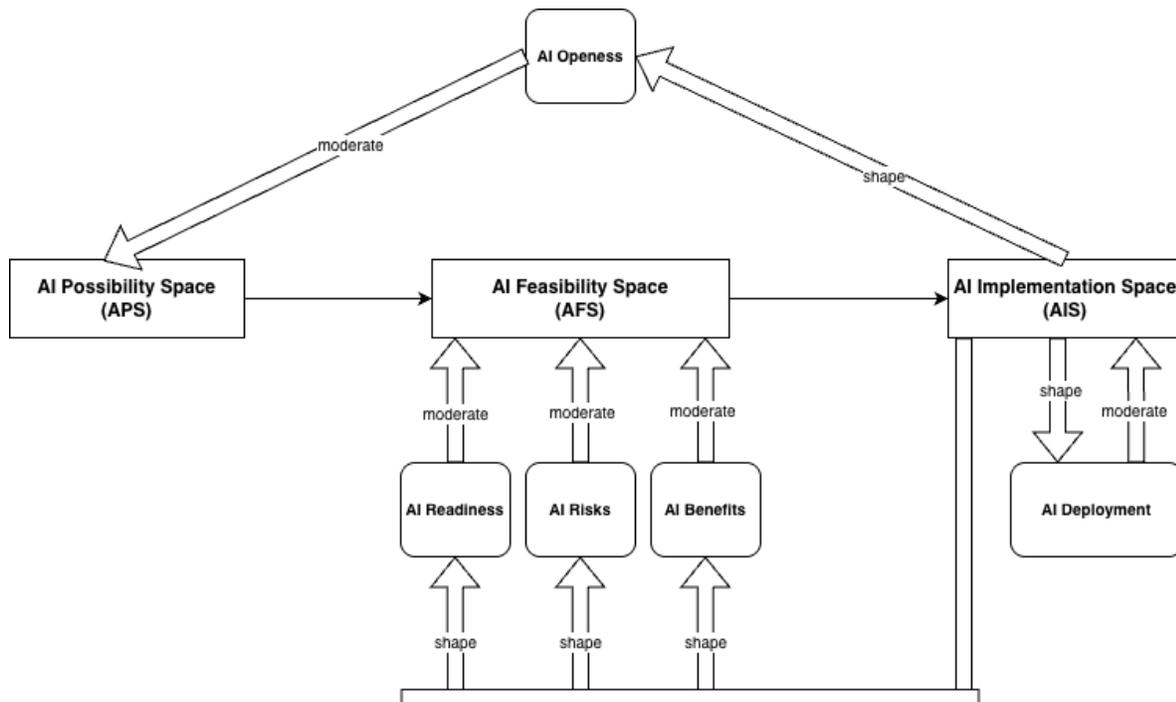
### 1.3.1 AI Strategy Framework (AISF)

**Figure 3** illustrates the AI Strategy Framework (AISF) scheme, which systematically synthesizes our findings from previous sections. Below we will review specific constructs and concepts of the AISF. The framework explains how game companies identify AI opportunities, assess their feasibility, and ultimately integrate them, while continuously learning and adapting from implementation outcomes.

At the foundation of the AISF lies the concept of AI which we defined in section 1.1.1. through the product lifecycle lens as *“a set of AI-labelled technologies that can be applied to enhance the efficiency of any stage of the game lifecycle”*.

The AISF starts with the **AI Possibility Space (APS)**, representing all AI applications that are possible within the gaming industry at a given time. The APS concept consolidates the taxonomy presented earlier in section 1.1.2. and includes use cases across game creation (e.g., ideation, asset generation, coding, QA, localization), game delivery (e.g., marketing, analytics, community management, support, fraud detection, live-ops) and Play/Runtime (e.g., NPC behaviour, dynamic difficulty adjustment, procedural content generation, visual enhancement, matchmaking).

**Figure 3. AI Strategy Framework**



*Source:* Prepared by the author based on the results of theoretical rationale

However, game studios differ in their ability to identify and use these possibilities. The extent to which a game studio can translate the APS into actionable opportunities depends primarily on its **AI Readiness** (TOE and Dynamic Capabilities) and two other moderators - **AI Benefits** (the value expected from AI) and **AI Risks** (dilemmas and challenges that may constrain AI exploration). Together, AI readiness, AI benefits, and AI risks determine the scope of the **AI Feasibility Space (AFS)** - the subset of possible applications that appear realistic and reasonable for a given game studio.

Within this feasibility domain, the AI use cases remain only feasible for opportunities unless they are moved to execution. AI Deployment, encompassing process strategies (Agile, Lean), individual strategies (UTAUT, TAM, DOI) and ecosystem strategies (OI, RDT), moderates the translation of feasible opportunities into specific activities of the firm, giving rise to the **AI Implementation Space (AIS)**. The AIS represents the realized AI practices within the game studio.

Successful implementations within the AIS are not endpoints but feedback mechanisms that inform the next strategic cycle. Outcomes from the AIS contribute to organisational AI Readiness, refine AI Deployment and shape perception of AI risks and AI benefits.

Moreover, the AIS contributes not only internally but also to the broader game industry frontier. As innovative practices diffuse, what was once exceptional becomes the industry standard, reshaping the set of possibilities for incumbents. Moderated by **AI Openness** (open innovation, game industry perception of AI, visibility of success stories) achievements of the specific game studio can expand the industry's collective APS.

Overall, the AI Strategy Evolution Framework positions AI-driven transformation as an iterative and co-evolutionary process, where technological innovation and strategic adaptation reinforce each other. The gaming industry, characterized by rapid experimentation, visible innovation diffusion, and close ties between technology and creativity, provides an ideal context for this model. By integrating technical readiness, managerial action, openness, and contextual perceptions into one cyclical system, the AISF captures how AI both shapes and is shaped by entrepreneurial strategies.

### 1.3.2. Hypothesis

Based on the AISF, we will make hypotheses for our research questions. The hypotheses derived from the AISF collectively describe the dynamics through which AI-related capabilities and perceptions shape strategic development in game companies.

The first question of our research is the specific practices which game companies should implement to ensure AI implementation. Based on the AISF we can see that AI implementation depends on the company's AFS and the AIS. Therefore, the practices should improve these constructs of our framework.

*H1: Game companies should use AI exploration practices to broaden their AFS.*

*H2: Game companies should use AI deployment practices to achieve a higher conversion rate from the AFS to the AIS.*

The second question of our research concerns the **strategic challenges** that must be resolved before AI adoption can effectively begin. According to the AISF, the launch of the framework depends on a company's ability to build a sufficient AI strategic baseline encompassing readiness, deployment competence, and balanced perceptions of AI risks and benefits.

*H3: Game companies should reach a minimum threshold of AI strategic baseline to launch the AISF: AI readiness, AI Deployment competences, perception of AI Benefits, and perception of AI Risks.*

The third question of our research is what strategic decisions favour better AI adoption. In the AISF, this improvement depends on the firm's ability to transform implementation outcomes (AIS) into knowledge that continuously strengthens its strategic baseline and contributes to industry learning through AI Openness.

*H4: Game companies should ensure that AIS feed knowledge back to AI strategic baseline to ensure that the AISF loop becomes self-reinforcing and evolves over time.*

The theoretical framework described in this chapter guides our research methodology. Because we focus on the "how" question, the study is based on a qualitative case study. The unit of analysis is the firm, specifically a B2C gaming company, as entrepreneurial strategy, AI implementation, and organisational decision-making are shaped at the firm level. This approach is consistent with the conceptual framework presented here. Our methodology is described in more detail in the next chapter.

The hypotheses formulated above are primarily intended as guiding expectations about how AI strategy evolution should unfold in game companies. Given the qualitative single-case design, they are not treated as statistically testable propositions but rather as predicted patterns that can be compared with empirically observed patterns.

## **2. RESEARCH DESIGN AND METHODOLOGICAL APPROACH**

In this chapter, we present our methodological approach.

Section 2.1 outlines and justifies the research design, explaining why the case study method is appropriate for our research. We also describe the criteria used to select the case and its temporal boundaries of the study.

Section 2.2 details the data collection procedures. We make an overview of each type of data source collected for the period 1 January 2020 to 31 August 2025, including company reports, press releases, earnings call transcripts, public interviews, keynote presentations, internal research papers, and complementary external materials. For each source category, we describe the search strategies, inclusion criteria, and relevance to the research questions.

Finally, Section 2.3 explains how the collected data were analysed. We describe the workflow used to organise the material in Zotero, the coding procedures carried out in Atlas.ti, and the hybrid human-AI approach that combined manual coding with LLM-assisted preprocessing.

### **2.1. Research Method**

In Section 2.1, we describe and justify the research method adopted in this thesis. We outline the rationale for the chosen research design, details the criteria guiding case selection, and defines the temporal boundaries of the study.

#### **2.1.1. Justification of Research Methods**

Given the nature of the research questions, the case study method is the most appropriate methodological choice for this thesis. The research questions are exploratory and descriptive rather than binary, as they examine how AI shapes strategic practices, decisions, and challenges within game companies. Qualitative designs (particularly case studies) are well suited for addressing “how” and “why” questions and when the boundaries between a phenomenon and its real-life setting are not clearly defined, the case study becomes the preferred strategy of inquiry (Ghauri et al., 2020).

Accordingly, this thesis employs a case study research design. While we were not able to identify peer-reviewed studies that use case studies specifically to examine AI implementation in the gaming industry (with the exception of a non-peer-reviewed study by Barczak and

Kwiatkowska (2025) ) several recent studies have applied case study methodology to analyse the adoption of new technologies in organisational and entrepreneurial contexts (Piepponen et al., 2022; Feulner et al., 2025; Ardolino et al., 2025). These works demonstrate that the case study approach is well established for examining emergent technologies and strategic adaptation, which aligns closely with the aims of this thesis.

### **2.1.2. Case Selection**

Our unit of study is a firm - specifically, a company in the game industry focused on the production and distribution of video games (B2C). To meet the research goal and ensure high-quality results, the chosen case must satisfy the following criteria:

- **AI-advanced:** the firm must be driven by AI, meaning it demonstrates real AI use cases, has identifiable AI implementation processes, and incorporates AI into its strategic agenda. Companies without a clear focus on AI would not provide data relevant to our research.
- **Data-rich:** sufficient publicly available information must exist to enable a thorough investigation.

Multinational corporations typically provide a richer data environment due to extensive reporting, documentation, and media visibility. However, they are generally more difficult to access for direct interviews compared SMEs (Ghuri & Firth, 2009). SMEs, in contrast, are often easier to reach but usually lack the depth and breadth of publicly available data. For the purposes of our study, we prioritise cases with substantial AI applicability and at least a five-year operational history. This timeframe allows us to compare the firm's behaviour before and after the recent AI-hype period, helping us analyse how the emergence and wider spread of AI technologies influenced strategic decisions.

For these reasons, we select a multinational corporation as our primary case study and begin by analysing all publicly available AI-related information. We will attempt to reach employees of this corporation for direct interviews. However, if direct access cannot be established, we will base our research solely on documentation and other publicly available information, which is an acceptable and recognised approach in case study research (Cheong et al., 2023).

We start with a single-case study design for reasons of time efficiency. A single case is justified when the case is critical, extreme/unusual, common, or revelatory (Yin, 2018). In our situation, we select a case that is both critical and common. We considered several large

companies that meet our criteria: EA Games (USA), Ubisoft (France), and Krafton (South Korea). All three are data-rich and have demonstrated substantial commitment to AI in their business models and development pipelines. However, we choose EA Games for this thesis because nearly all its relevant documentation is available in English, which simplifies the research process. While both Krafton and Ubisoft also publish a significant amount of material in English, an initial review showed that some important items (such as company reports) are available only in Korean or French, which may complicate systematic data collection.

To summarise, our case study will examine the AI-related activities and strategic responses of EA Games before and after the release of the ChatGPT chatbot, based on GPT models, on November 30, 2022 (OpenAI, 2022). We will focus on the period from 1 January 2020 to 31 August 2025, allowing us to analyse a substantial timeframe both prior to and following the “AI Spring.” This event is selected as a focal point because it can be interpreted as a structural shock to the APS, potentially triggering a new iteration of the AISF cycle. Throughout the research, we analyse what the company did in relation to AI, which decisions were taken, how entrepreneurial strategies evolved, and how these developments align with our hypotheses and the AISF framework presented above.

The full case study protocol was developed following the structure proposed by Yin (2018) and is provided in Annex 1.

## **2.2. Data collection**

Data collection began with the creation of a case study database, an essential step for ensuring the reliability and transparency of case study research (Yin, 2018). All documents relevant to the case were first retrieved and stored in Zotero, where they were reviewed, pre-processed, and organised. After the initial screening, the materials were uploaded into Atlas.ti (web version), developed by Scientific Software Development GmbH, to support systematic coding and analysis. A naming convention and sorting logic were established to ensure consistent organisation of materials in the case study database (Annex 2).

To strengthen the construct validity of the study (Yin, 2018), we employed data triangulation, understood as the use of multiple data sources to examine the same phenomenon (Ghauri & Firth, 2009). This approach is particularly important in research areas characterised by technological uncertainty, such as AI adoption in the gaming industry. Following the logic of triangulation, potential data sources were identified by first reviewing the types of evidence used in prior studies on similar topics. This included examining methodological choices in existing

research on AI in gaming, entrepreneurial strategy, and technological innovation, allowing the selection of diverse and complementary forms of evidence.

As mentioned above, we were focused on data sources for the period between 1 January 2020 and 31 August 2025.

### **2.2.1. Company reports**

Gao et al. (2025) argue that annual reports are a credible source of information for examining how companies utilise artificial intelligence, as such reports are formally reviewed and publicly audited. Following this reasoning, we collected Electronic Arts' annual reports directly from the company's official website. As EA is a publicly listed company in the United States, it is legally required to submit periodic filings to the Securities and Exchange Commission (SEC), including Form 10-K and other disclosures. These filings provide detailed, standardized information on the company's operations, risks, and strategic priorities, which makes them a valuable source for analysing AI-related activities. Accordingly, we retrieved EA's 10-K reports from the official SEC database.

We also collected EA's annual Proxy Statements of EA. Proxy statements provide information on corporate governance, executive compensation, board composition, and shareholder voting matters. While not directly focused on technological capabilities, these documents offer important contextual insights into leadership priorities and governance structures that may influence strategic decisions regarding AI adoption and investment.

A further type of report included in our dataset was EA's Impact Report, which provides insights into the company's broader strategic initiatives, sustainability commitments, and organisational practices. These reports complement 10-k reports and proxy statements by revealing non-financial dimensions of EA's strategy, including potential areas where AI may be relevant.

### **2.2.2. Press releases**

Press releases constituted another important source of information, as they often contain timely announcements about strategic initiatives, partnerships, technological developments, and organisational changes. However, EA has published several thousand press releases over the examined period, making a manual review infeasible. To address this, we developed a structured search strategy aimed at retaining only those materials relevant to our research focus while

excluding press releases unrelated to technological or strategic issues (e.g., purely financial results, esports announcements, community updates, or game updates without technological implications).

To conduct this search, we created four topic clusters with associated keyword sets (**Table 2**). These clusters were designed to capture core dimensions relevant for our research.

**Table 2. Topic Clusters for Data Search**

Cluster Name	Cluster Description	Search query	Found Sources (number)
Cluster 1: General Business Strategy	All communications where EA discusses its strategic direction, long-term goals, leadership vision, or corporate priorities.	("strategy" OR "priorities" OR "vision" OR "roadmap" OR "leadership" OR "investment" OR "goals" OR "transformation" OR "restructuring")	74
Cluster 2: Internal Conditions for Technology Adoption	EA's internal capability-building, infrastructure modernization, organisational processes, and readiness signals.	("infrastructure" OR "capabilities" OR "workflow" OR "modernization" OR "systems" OR "engineering")	37
Cluster 3: AI related topic	All communications that mention AI technologies.	("AI" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "LLM" OR "diffusion" OR "GAN" OR "VAE" OR "autoencoder" OR "reinforcement learning" OR "imitation learning" OR "evolutionary" OR "procedural" OR "PCG" OR "algorithm")	18
Cluster 4: External Actors	Announcements involving external actors (partnerships, collaborations, licensing	("partner" OR "collaboration" OR "alliance" OR "acquisition" OR "cooperation" OR	63

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deals, and acquisitions) to "integration" OR "licensing" OR  
 reflect EA's openness to "pilot")  
 external AI ecosystems

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TOTAL 192

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*Source:* Completed by author

Using Google's site-specific search functionality, we applied these keyword clusters to EA's investor-relations website (site:ir.ea.com/press-releases), with the time window restricted to 1 January 2020 - 30 September 2025.

We found 192 sources. After removing duplicates (89), 103 unique press releases remained. An in-depth relevance review further reduced this set to 18 press releases that directly contributed evidence to the research questions.

### **2.2.3. Earnings call transcripts**

Earnings calls are quarterly conference calls in which senior executives present the company's financial performance and respond to questions from analysts and investors. They are valuable sources of data because they provide real-time insights into managerial interpretations of strategic developments, organisational priorities, and emerging opportunities or risks. Unlike formal regulatory filings, earnings call transcripts often include forward-looking statements, qualitative explanations, and unscripted discussions that reveal how decision-makers understand ongoing technological and market shifts.

The transcripts of these calls are publicly available on EA's official investor relations website (<https://ir.ea.com/financials/quarterly-results/default.aspx>). Transcripts for all quarters from 2020 to 2025 were retrieved and included in the case study database.

### **2.2.4. Public interviews**

Public interviews and other talks featuring company executives is a valuable source of data. Such materials provide direct insights into how leaders articulate strategic priorities and organisational responses to industry trends. Haefner et al. (2023), for example, used podcast episodes with industry representatives as data sources to analyse AI implementation across

companies, demonstrating the methodological relevance of executive interviews for studying emerging technologies.

To identify relevant interviews, we developed a structured search strategy using Google Video Search and Google News Search. Our queries included: (1) a reference to Electronic Arts, (2) a reference to the interview format, and (3) the names of key EA executives. Date limits were set to match the research period. The final search string was:

*("Electronic Arts" OR EA) ("interview" OR "Q&A" OR "podcast") ("Andrew Wilson" OR "Laura Miele" OR "Vijaye Raji" OR "Ken Moss" OR "Samantha Ryan" OR "David Tinson" OR "Magnus Nordin" OR "Audrea Topps-Harjo" OR "Mike Mahar" OR "Christian Cimon" OR "Per Magnusson" OR "Steven Kah Hoo Ong" OR "George Parrish" OR "Hyunsoo Woo" OR "Stephanie O'Malley Deming" OR "Javier Rivos")*

For the video search, we additionally filtered results by duration to exclude very short clips, fragments, or promotional cut-outs that were not meaningful interview formats. This resulted in two lists: videos  $\geq 4$  minutes (204 results) and videos  $\geq 20$  minutes (77 results). Each item was manually reviewed for relevance. After removing unrelated materials and non-interview formats (e.g., commentary videos, edited recaps), 7 videos remained.

In the Google News search, 38 results were identified, of which 4 met the relevance criteria after manual screening.

In total, we collected 11 public interviews with EA executives for inclusion in the case study database.

### **2.2.5. Keynotes**

Keynote presentations and conference talks constitute another valuable source of data, as they provide direct insight into how companies publicly communicate their technological vision and innovation priorities. Unlike interviews, which are often reactive and question-driven, keynotes typically reflect carefully prepared speeches that highlight an organisation's long-term and emerging capabilities. For this research, keynotes are particularly relevant because they often include demonstrations of new technologies, explanations of internal processes, and high-level discussions on AI-driven transformation in the gaming industry.

We identified EA's keynote presentations through the GDC Vault platform (<https://gdcvault.com>), one of the most comprehensive repositories of professional talks in the

game development industry. Using keyword-based search and manual screening, we selected 16 video presentations that address AI-related themes and are relevant to our research questions. These videos were subsequently added to the case study database for detailed analysis.

### **2.2.6. Research Papers**

Research papers produced by EA's internal R&D teams represent an additional category of valuable data. These publications offer detailed technical insights into the company's experimental work, methodological approaches, and innovation priorities in the field of artificial intelligence. R&D papers provide concrete evidence of the tools, models, and algorithms being developed or tested within the organisation. They therefore serve as an important complementary source for assessing EA's technological capabilities and readiness for AI adoption.

Through EA's official research portal (<https://www.ea.com/technology/research/ai-machine-learning>), we identified 19 research papers related to AI and machine learning. All retrieved documents were added to the case study database for subsequent coding and analysis.

## **2.3. Data analysis**

All collected documents were first imported into Zotero, where they were sorted into collections according to data type. This organisational structure enabled consistent processing of each category of materials (for example, regulatory reports were reviewed as one collection, press releases as another). Following this pre-processing stage, the data was transferred into Atlas.ti (web version) for coding. Each document was renamed according to the established naming protocol, and coding was originally performed manually. However, the substantial volume of data made a fully manual workflow inefficient.

Recent research suggests that large language models (LLMs) can support qualitative analysis by accelerating coding tasks, identifying patterns in unstructured data, and providing preliminary interpretations that researchers can subsequently verify (Zhang et al., 2025). In line with this perspective, we do not treat LLMs as a replacement for human analysis but as an auxiliary tool to increase efficiency while maintaining full researcher oversight. After testing several workflows, a hybrid approach using Google NotebookLM proved to be the most productive.

A dedicated NotebookLM environment was created, and key contextual materials were uploaded to ensure alignment with the research design: the theoretical chapter of this thesis, case study protocol, naming convention. Data collections were then uploaded and processed

sequentially (e.g., Form 10-K filings first, followed by press releases, etc.). For each collection, NotebookLM was prompted to propose document names consistent with the naming convention (prompt: *“Rename all [data type] according to our naming convention. Output format: table with columns ‘old name’, ‘original name’”*).

Next, each source was analysed using a structured extraction prompt (e.g., *“Review [source name] and list all quotes relevant to our research topic. Output in a table with columns ‘Quote’ and ‘Explanation of relevance’”*). To verify reliability, a random subset of documents from each collection was manually reviewed. While occasional omissions were identified, they were infrequent and did not concern critical material.

After the extraction stage, all documents were imported into Atlas.ti, renamed according to NotebookLM’s output, and organised into groups based on temporal phase (pre-AI Spring vs. post-AI Spring) and source type (reports, press releases, interviews, etc.). The tables with quotes generated by NotebookLM were then manually reviewed, validated, and relevant quotes were manually coded in Atlas.ti. Following each coding cycle, the updated codebook was uploaded back into NotebookLM to enhance the model’s contextual awareness for subsequent collections.

This hybrid workflow enabled efficient handling of a large dataset while ensuring analytical accuracy and methodological transparency.

Our codebook is provided in Annex 3.

### 3. CASE STUDY FINDINGS AND ANALYSIS

In this chapter, we present our research findings and their analysis.

Section 3.1 presents an overview of the case study. It provides general information about the object of study (Electronic Arts) and establishes the necessary context for the subsequent analysis.

Sections 3.2-3.4 analyse the findings from the perspective of the research questions (RQ1-RQ3). In Section 3.2, we identify AI applications adopted by Electronic Arts (RQ1). We then retrieve and analyse the risks and challenges related to AI adoption in Electronic Arts in Section 3.3 (RQ2). Section 3.4 presents empirical findings related to entrepreneurial strategies (RQ3) that Electronic Arts applies in the context of AI adoption.

Section 3.5 integrates the findings presented in this chapter. It introduces the AI Implementation Model for Electronic Arts and compares it with the AI Strategy Framework developed in Section 1.3.1. In addition, this section reflects on the hypotheses formulated in Section 1.3.2 by comparing them with the empirically observed patterns in Electronic Arts.

Finally, Section 3.6 outlines the limitations of the research, which follow from the research design and affect both the scope of the conclusions and the extent to which the results can be generalized beyond the studied context.

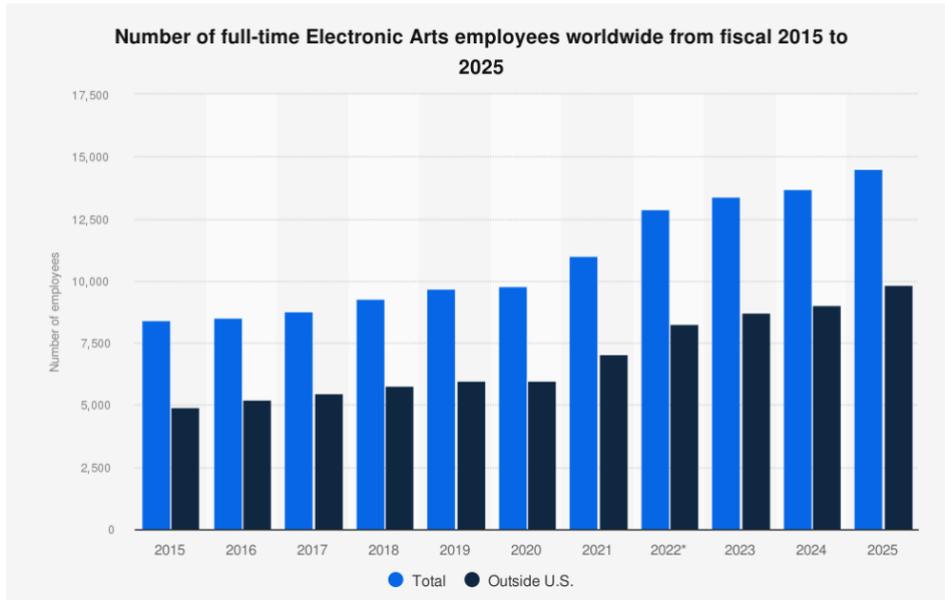
#### 3.1. Case Overview

Electronic Arts (EA) is one of the largest and most established game developers and publishers globally with headquarters in USA (Redwood City, California).

Electronic Arts can be considered one of the largest players in the global gaming market.

As of the end of 2025, Electronic Arts employed approximately 14,500 people, the majority of whom were located outside the United States (**Figure 4**).

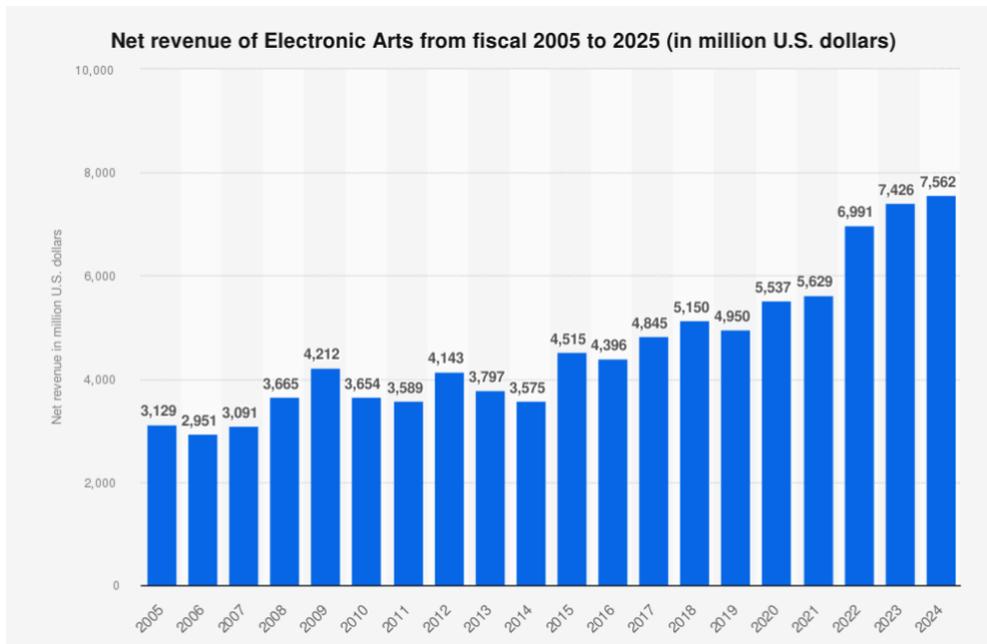
**Figure 4.** Number of full-time Electronic Arts employees worldwide



Source: Statista (2025)

Electronic Arts reported revenue of 7.46 billion U.S. dollars in its 2024 fiscal year (**Figure 5**).

**Figure 5.** Net revenue of Electronic Arts from fiscal 2005 to 2025



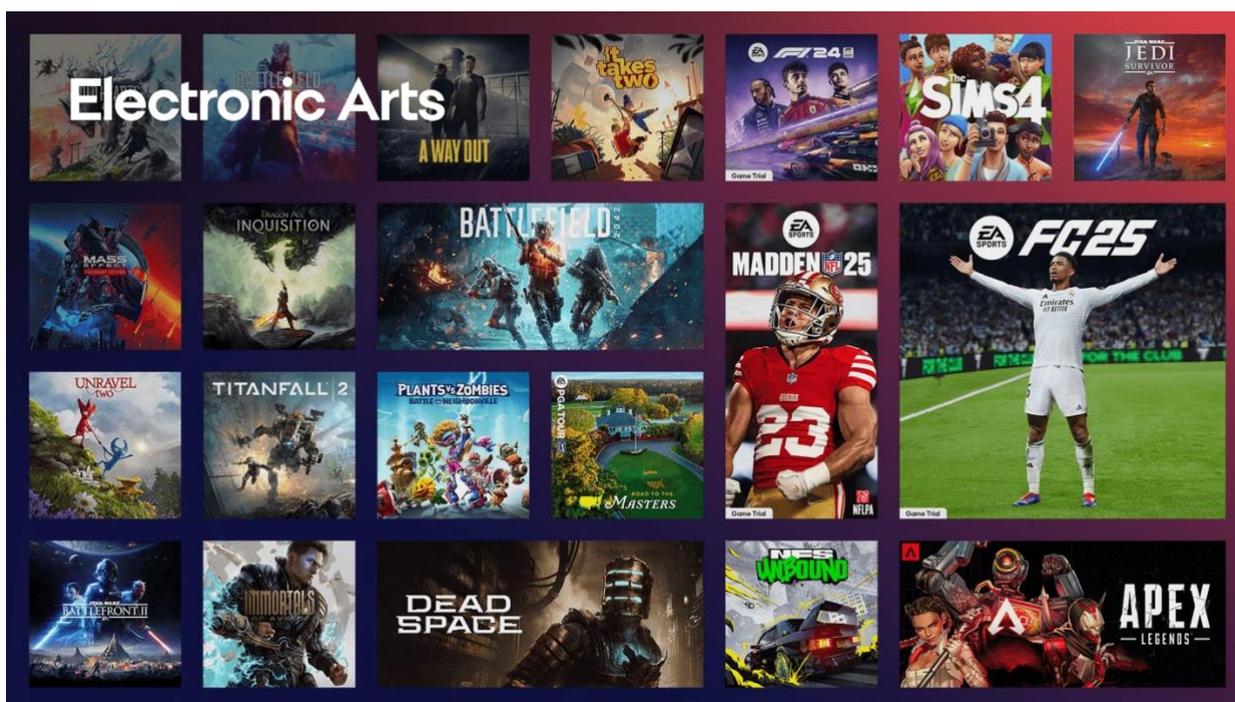
Source: Statista (2025)

In general, Electronic Arts focuses its strategy on several key areas, including further expansion of its game portfolio with a strong emphasis on mobile platforms, the development of social tools for its community, the utilization of social ecosystems surrounding its games, and expansion into new platforms and business models (Electronic Arts, 2021e; Electronic Arts, 2021k; Fortune Magazine, 2022; Electronic Arts, 2022d; Electronic Arts, 2022e; Electronic Arts, 2023e; Electronic Arts, 2023g).

In this connection, Electronic Arts demonstrates extreme diversity in terms of its product portfolio, gaming platform and business models.

The company has one of the biggest game-portfolio in the industry (**Figure 6**). Company's own IP include Apex Legends as well as such famous franchises as the Sims and Battlefield. Licensed-IP include games on such franchises as Star Wars and EA sports. EA sport is a line-up of various sports games which rely on the ecosystem of licensed content from major sport leagues (FIFA, Formula 1, NHL, UFC) and other sport event organisers. In general, Electronic Arts considers FC (formerly FIFA) and Apex Legends to be its key projects (Electronic Arts, 2022j).

**Figure 6. Game Portfolio of Electronic Arts**



*Source: McGee (2025)*

EA's games are available on all major platform such as consoles, PC and mobile, herewith expansion to mobile platforms was a significant part of company's strategy during last years.

EA games demonstrate a huge variety of business models. Live Services business model generates the biggest amount of revenue for EA games and is used in its key major franchises - EA Sports FC (ex-FIFA) and Apex Legends. In addition, company also utilizes business models with single game purchase, free-to-pay and subscriptions (Electronic Arts, 2020d).

Electronic Arts identifies several major industry trends that influence its strategy and business decisions:

- A growing shift from physical to digital consumption of games (CNBC Television, 2020; Electronic Arts, 2022d);
- Increased accessibility of gaming and the rising popularity of interactive entertainment (CNBC Television, 2020; The Game Awards, 2021; Electronic Arts, 2022b; Electronic Arts, 2022c; CNBC Television, 2023);
- The growing value attributed to each individual player (Vanian, 2021).

The case of EA was analysed in relation to the main research questions of our thesis - how AI shape entrepreneurial strategies in the gaming industry - and three supporting research questions regarding AI implementation practices (RQ1), strategic challenges of AI implementation (RQ2) and improved of entrepreneurial strategies when adopting AI (RQ3). Accordingly, our analysis is structured around RQ1-RQ3. The interpretation of findings is informed by the AISF, which provides an analytical lens for understanding the interaction between AI adoption and such factors as company's technological possibilities, organisational feasibility, implementation choices as well as perception of AI's risks and benefits.

A central analytical feature of our study is its temporal perspective. The analysis adopts a comparative pre- and post-event logic centred on the significant improvement and public interest in generative artificial intelligence in late 2022, commonly referred to as the "AI Spring." A key milestone in this period was the public release of ChatGPT on 30 November 2022, which significantly lowered the barriers to accessing advanced AI capabilities and accelerated experimentation across many industries. In the context of this research, the AI Spring is treated as a strategic point that expanded the range of AI-related opportunities available to game studios, while simultaneously reshaping feasibility conditions, risk perceptions, and entrepreneurial decision-making processes. The empirical analysis is based on multiple publicly available data

sources that document EA's strategic priorities and various activities related to our research. These include corporate reports and regulatory filings, earnings call transcripts, official EA blogs and technical publications, public interviews and conference presentations by executives and other employees. Together, these materials provide the empirical foundation for analysing how AI-related practices, constraints, and decision-making processes evolved at EA before and after the AI Spring.

### **3.2 AI Applications adopted by Electronic Arts**

In Section 3.2, we address RQ1 by examining the AI practices adopted by Electronic Arts. Building on the theoretical framework developed in the previous Section 1.1., we analyse how Electronic Arts applies AI across different stages of the game lifecycle: game creation, game delivery, and runtime/play. The analysis seeks to determine whether AI applications are more concentrated in specific lifecycle stages or whether they are distributed relatively evenly across the game lifecycle at Electronic Arts. In addition, we examine whether there are systematic differences in AI applications between the pre-AI Spring and post-AI Spring periods. Finally, this section synthesizes the empirical findings and presents an AI application model for Electronic Arts.

#### **3.2.1. AI Applications for Game Creation**

AI applications for game creation at Electronic Arts are dominated by AI-based testing in both the pre-AI Spring and post-AI Spring periods.

In the pre-AI Spring period, Electronic Arts placed substantial emphasis on AI testing in its research output. EA-affiliated researchers described the application of reinforcement learning agents to maximize automated playtesting (Gordillo et al., 2021) and extended these approaches through imitation learning techniques (Sestini et al., 2022). Testing is also explicitly discussed as a key AI use case by EA SEED's General Manager Uma Jayaram, who refers to reinforcement learning in the context of quality assurance (MIT TR Arabia, 2021). The application of AI for testing in EA games is further confirmed by a later keynote by EA's principal engineer Jonas Gillberg, who mentions the use of "autoplayers" in earlier Electronic Arts titles (Gillberg, 2023).

In the post-AI Spring period, AI for testing remains the most frequently mentioned AI use case within the game creation stage. Notably, Jonas Gillberg delivered a keynote, mentioned above, fully dedicated to the use of AI for testing at Electronic Arts (Gillberg, 2023). In parallel,

EA-affiliated researchers increasingly discuss the application of more advanced AI techniques for testing purposes. For example, imitation learning is further developed and presented as a more mature and effective approach for testing, as reflected in multiple EA research publications (Ahlberg et al., 2023; Sestini et al., 2023). This demonstrates continuity between pre- and post-AI Spring research trajectories within EA. The importance of AI-based testing is also acknowledged at the executive level: EA's CEO Andrew Wilson explicitly refers to AI testing in a public interview (Rapid Response, 2024) and implicitly in the context of the launch of Battlefield Labs, a community-driven testing program for the Battlefield franchise (Electronic Arts, 2025a). For the first time, AI testing is also mentioned in an official company report in the post-Spring period (Electronic Arts, 2025h). Overall, the evidence indicates that the role of AI in testing processes at Electronic Arts has expanded significantly over time.

Another important AI application within the game creation stage is asset creation. In the pre-AI Spring period, references to AI for asset creation are limited to isolated research efforts, such as work on 3D face reconstruction (Deng et al., 2022) and asset quality verification (Tamm et al., 2022). These sources do not allow us to conclude that AI was used in day-to-day asset production at EA during the pre-Spring period. However, they do indicate that AI research related to asset creation was already an area of interest for EA specialists.

In contrast, the post-AI Spring period provides multiple indications that AI has been incorporated into asset creation in Electronic Arts' operational practices. Several press releases highlight the use of procedural terrain generation tools (Electronic Arts, 2023b) and Sapien technology for character likeness and realism (Electronic Arts, 2024c). Multiple sources describe how generative AI is used within EA Sports franchises to render in-game characters (athletes) and environments (stadiums). These applications are discussed across a range of materials, including Impact Reports (Electronic Arts, 2024i; Electronic Arts, 2025h), earnings calls (Electronic Arts, 2024d), and interviews with the CEO (Rapid Response, 2024). This convergence of sources demonstrates that post-AI Spring asset creation use cases are widely acknowledged and institutionally validated.

AI for culturalization (i.e., localization) is mentioned only once in the post-AI Spring period (Rapid Response, 2024). However, this reference appears to be largely conceptual and does not find confirmation in other sources indicating actual or systematic use. In a similarly hypothetical manner, the use of AI for user-generated content is mentioned in the post-AI Spring period (Rapid Response, 2024). This application can be interpreted as a highly specific sub-case of asset creation. However, the reference remains conceptual and is not supported by evidence of concrete implementation in other sources.

Additionally, from 2023 onward, Electronic Arts makes more general references to the incorporation of AI into its development processes, including in several company reports (Electronic Arts, 2023h; Electronic Arts, 2024i; Electronic Arts, 2024h; Electronic Arts, 2024d; Electronic Arts, 2025g; Electronic Arts, 2025i).

Taken together, the evidence shows that testing and asset creation constitute the two key AI application domains within the game creation stage at Electronic Arts.

### **3.2.2. AI applications for Game Delivery**

In the game delivery stage, fraud detection emerges as an AI use case both before and after the AI Spring. Early evidence comes from research papers examining the use of Isolation Forest techniques to identify suspicious player behaviour in multiplayer games (Greige et al., 2022). In addition, AI-based fraud detection is implicitly referenced in pre-Spring corporate disclosures, such as the 10-K report, which mentions the monitoring of disruptive behaviour through “detection models” (Electronic Arts, 2022h). Post-AI Spring, similar applications appear in the context of EA’s anti-cheat systems, including references in Impact Reports (Electronic Arts, 2023i; Electronic Arts, 2024i) and the introduction of the newer EA Javelin Anti-Cheat system (Electronic Arts, 2025h).

Within the same domain, it is also worth noting the use of natural language processing for sentiment analysis in the pre-Spring period, as mentioned in a keynote by EA SEED’s General Manager Uma Jayaram (MIT TR Arabia, 2021).

AI-driven personalisation is discussed less frequently. One explicit reference appears during earnings call in May 2025 (Electronic Arts, 2025e). Additional implicit references to recommendation systems can be found in the context of Madden NFL 26, particularly regarding smart play recommendation features (Electronic Arts, 2025j; Electronic Arts, 2025b).

Overall, fraud detection appears to be the most frequently evidenced AI use case within Electronic Arts’ game delivery activities. However, compared to game creation use cases, AI applications in game delivery are generally described at a higher level of abstraction and are less explicitly documented in the available source materials.

### **3.2.3. AI Applications for Runtime/Play**

AI usage at the runtime/play stage is characterized by several key application areas.

The first group can be broadly categorized as AI for gameplay systems. In the pre-AI Spring period, references to this use case appear primarily at a general or implicit level. A general indication is provided by Uma Jayaram (MIT TR Arabia, 2021), followed by more specific but still indirect examples. These include the Dynamic Gameday feature in Madden NFL 22 (Electronic Arts, 2021f) and the FieldSENSE™ Gameplay System introduced in Madden NFL 23 (Electronic Arts, 2022g).

In the post-AI Spring period, mentions of AI for gameplay systems become more frequent and, in contrast to the pre-Spring period, more explicitly framed as AI-driven. AI for gameplay is directly referenced in relation to several major titles, including EA Sports FC 25 (Electronic Arts, 2024d), EA SPORTS NHL 25 (Electronic Arts, 2024c; Electronic Arts, 2024a), and Madden NFL 26 (Electronic Arts, 2025c).

Within the broader category of AI for gameplay systems, two more specific sub-cases can be distinguished: AI for non-player characters (NPCs) and AI for game navigation. Early references to AI for NPCs appear in EA-affiliated research, such as work on MultiCriticAL, which focuses on smooth transitions between behavioural styles (Mysore et al., 2022), followed by a general mention in Uma Jayaram's keynote (MIT TR Arabia, 2021). Post-AI Spring, references to AI for NPCs become both more frequent and more concrete, appearing across multiple sports titles and technologies. Examples include FC IQ in EA Sports FC 25 (Electronic Arts, 2024k), ICE-Q in EA SPORTS NHL 25 (Electronic Arts, 2024a), QB DNA and Coach DNA in Madden NFL 26 (Electronic Arts, 2025j; Electronic Arts, 2025b), and reinforcement learning-based gameplay systems referenced for EA Sports FC 26 (Electronic Arts, 2025k). Taken together, these examples indicate that AI for NPC behaviour is actively applied across the sports game portfolio of Electronic Arts.

With respect to AI for game navigation, only high-level indications are available. General references appear both in the pre-AI Spring period (MIT TR Arabia, 2021) and in the post-AI Spring period (De Schaetzen & Sestini, 2023; Electronic Arts, 2025h). However, no specific in-game implementations are explicitly described in the available sources.

A second major group of runtime AI applications relates to in-game animation. From 2021 onward, several sources explicitly reference EA's use of machine learning for animation, particularly in FIFA 22. These include descriptions of the HyperMotion technology (Electronic Arts, 2021b; Electronic Arts, 2021a) and direct references to neural networks used for cloth animation (MIT TR Arabia, 2021), including applications in Madden NFL 21 (Lewin, 2021). In 2022, more implicit references appear, such as HyperMotion2 technology for women's in-game movement in FIFA 23 (Electronic Arts, 2022a).

These industry references are complemented by EA-affiliated academic research on real-time AI animation, including work on modulation networks for real-time style modelling of human locomotion (Mason et al., 2022). In a more general form, AI-driven animation is also acknowledged in recent earnings calls, albeit without reference to specific implementations (Electronic Arts, 2025e).

In addition, several standalone AI use cases at the runtime stage can be identified. Procedural content generation appears exclusively at the research level in the early pre-AI Spring period (Gisslén et al., 2021). Another example is AI-based glitch detection, mentioned in a keynote as a general capability but without reference to specific in-game deployments (MIT TR Arabia, 2021). Further research-oriented applications include AI-driven data-based co-speech gesture generation (Yoon et al., 2022) and an implicit reference to dynamic difficulty adjustment in *Dead Space Remake* (Electronic Arts, 2023a) and *College Football 26* (Electronic Arts, 2025f).

Overall, the evidence indicates that AI has been applied broadly within Electronic Arts' runtime/play stage, with identifiable continuity from the pre-AI Spring period to the present. While early references are often implicit or research-oriented, post-AI Spring materials increasingly frame runtime systems explicitly as AI-driven, particularly within EA's sports game portfolio.

#### **3.2.4. Benefits of AI for Electronic Arts**

In addition to articulating concrete AI applications, Electronic Arts also explicitly discusses the benefits it derives, or expects to derive, from AI implementation. Understanding how these benefits are framed is important for interpreting the company's perception of AI and its strategic relevance.

First, AI is consistently perceived as a tool for production efficiency. This notion appears fragmentarily in the pre-AI Spring period and receives much broader recognition in the post-AI Spring period across a wide range of sources. Production-efficiency benefits are described in terms of AI enabling faster work processes (MIT TR Arabia, 2021), accelerating business operations (Electronic Arts, 2024g), and increasing development speed (Electronic Arts, 2023d). Efficiency enhancement is also explicitly identified as a core objective of AI integration into production workflows (Electronic Arts, 2025h). Importantly, management does not frame AI primarily as a cost-reduction tool, but rather as a means of doing things faster and more effectively (Rapid Response, 2024). This perspective is illustrated by a statement from CEO Andrew Wilson during an earnings call Q&A session, where he noted that the production timeline for certain game assets had been reduced from six months to six weeks (Electronic Arts, 2024f).

Within this efficiency narrative, generative AI is increasingly highlighted in post-AI Spring sources as a distinct AI-labelled technology. Management acknowledges that generative AI already has a positive impact on development processes and is expected to further accelerate game production (Electronic Arts, 2024i; Electronic Arts, 2025g). Company representatives also express the expectation that a majority of development processes will eventually benefit from generative AI integration (Electronic Arts, 2024f).

A second prominent narrative frames AI as a tool for enabling new experiences. In pre-AI Spring sources, this benefit is primarily articulated as the ability to build new worlds and novel gameplay experiences (MIT TR Arabia, 2021). In the post-AI Spring period, this narrative becomes more pronounced, with AI described as a means to expand product offerings (Electronic Arts, 2023h; Electronic Arts, 2023c), deliver new experiences (Electronic Arts, 2025g), and introduce new features and even new categories of entertainment (Rapid Response, 2024; Electronic Arts, 2025i). Similar to the efficiency discourse, generative AI is explicitly referenced as a technology capable of delivering richer experiences to a broader audience (Electronic Arts, 2023d).

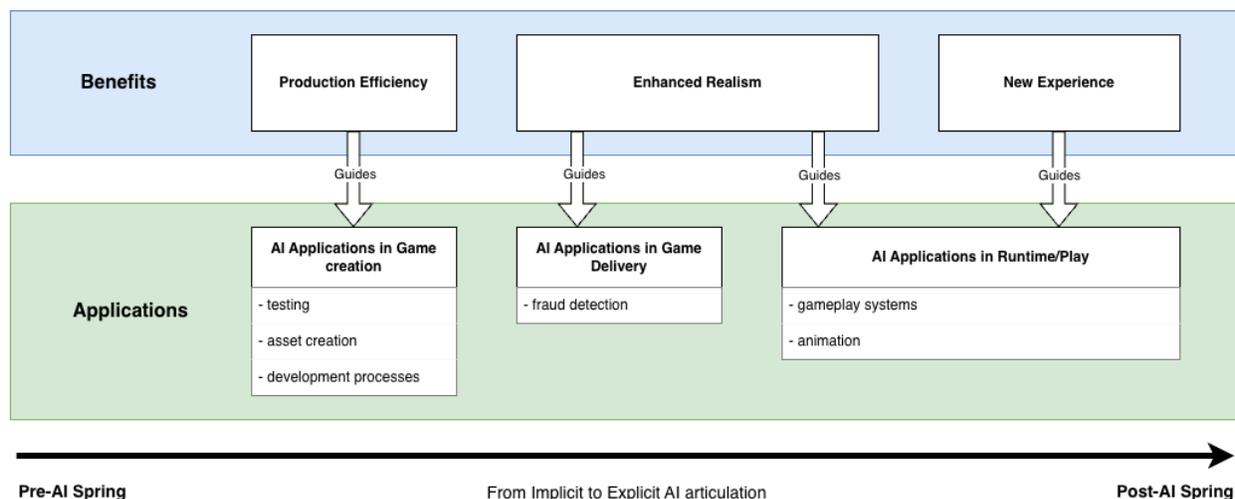
The third group of perceived AI benefits relates to enhancing realism in games. While this can be interpreted as a specific dimension of new experiences, it is treated separately here due to its frequent and consistent appearance in the source materials. In the pre-AI Spring period, Electronic Arts explicitly links AI usage to realism enhancement, particularly in the context of animation and physics-based systems (Electronic Arts, 2021b; Lewin, 2021). This emphasis continues in the post-AI Spring period (Electronic Arts, 2024d; Electronic Arts, 2024c). For EA's sports franchises in particular, AI-driven realism is framed as the ability to deliver more authentic and deeply immersive gameplay that mirrors the fluidity and intensity of real-world athletes and competition (Electronic Arts, 2025d; Electronic Arts, 2025e).

Overall, production efficiency, the creation of new experiences, and the enhancement of realism emerge as the three key categories of benefits that Electronic Arts associates with artificial intelligence.

### **3.2.5. Synthesis on AI applications practices**

Basing on our findings and observations in Sections 3.2.1. - 3.2.4. we can synthesize the AI application practices of Electronic Arts (**Figure 7**).

**Figure 7. Practices of AI Applications in Electronic Arts**



*Source:* Prepared by the author based on case study materials

The model demonstrates that AI applications at Electronic Arts are not evenly distributed across the game lifecycle. A higher concentration of AI use cases is observed in the game creation and runtime/play stages, while comparatively fewer applications are identified in the game delivery stage. This uneven distribution can be explained by the specific benefits that Electronic Arts associates with AI adoption, namely production efficiency, enhanced realism, and the creation of new experiences. These benefits manifest most clearly in game creation and runtime contexts, where AI can directly influence development workflows and gameplay systems, rather than in game delivery phase. Although the purpose of this research is not to provide quantitative validation, it is nevertheless possible to state that, in the case of Electronic Arts, there is an observable alignment between the perceived benefits of AI and the areas in which AI applications are most actively deployed.

Second, a temporal perspective reveals changes not only in AI applications themselves but also in how they are articulated and distributed across different types of sources. In the pre-AI Spring period, AI use cases are predominantly articulated implicitly and are largely confined to research papers, technical presentations, and keynotes, rather than being formally documented in official company reports. This pattern changes in the post-AI Spring period. During this phase, AI-labelled technologies are discussed more explicitly, and references to AI appear more frequently in corporate disclosures and official reports. In addition, generative AI increasingly

emerges as a distinct and explicitly named technology in post-AI Spring materials. In this sense, the observed shift may reflect either a substantial increase in the level of AI usage, a more explicit and formalized organisational articulation of AI within Electronic Arts, or a combination of both.

### **3.3 Challenges and Risks of AI Adoption**

In Section 3.3, we address RQ2 by examining the risks and challenges that shape the adoption and scaling of AI-related practices at Electronic Arts. The analysis reviews several groups of risks and challenges across key domains, including governance and legitimacy, infrastructure and data, talent and skills, and AI performance. The aim is to determine how Electronic Arts perceives AI-related risks and how these perceptions have evolved over time during the pre-AI Spring and post-AI Spring periods. The section concludes with a synthesis of the findings and the presentation of a risks and challenges model for Electronic Arts.

#### **3.3.1 Governance and Legitimacy Risks**

Electronic Arts consistently devotes substantial attention to regulatory and compliance risks, both in the context of its broad geographic footprint as a global operator and across multiple legal domains. Company reports from the pre-AI Spring period (Electronic Arts, 2020f; Electronic Arts, 2021h) repeatedly highlight a wide range of regulatory areas relevant to EA's activities, including electronic commerce, virtual items and virtual currencies, data protection and privacy, and consumer protection regulation. These disclosures also reference specific instances of regulatory scrutiny, such as law enforcement actions related to Ultimate Team modes within EA Sports franchises (Electronic Arts, 2020f; Electronic Arts, 2021h), particularly investigations by gambling authorities concerning the randomized distribution of virtual items (Electronic Arts, 2021h; Electronic Arts, 2022h). It is also worth noting that the Board of Directors pays specific attention to privacy-related risks (Electronic Arts, 2022i).

In the post-AI Spring period, AI emerges as a distinct regulatory domain within EA's risk disclosures. Starting in 2023, company reports explicitly address risks associated with the compliant incorporation of AI into games and development processes (Electronic Arts, 2023h; Electronic Arts, 2023c). This practice continues in subsequent years (Electronic Arts, 2024h; Electronic Arts, 2024j; Electronic Arts, 2025g), accompanied by direct acknowledgements of potential legal harm arising from improper or non-compliant use of AI technologies (Electronic Arts, 2025g). Electronic Arts further recognizes that new AI-specific regulations may be introduced,

or that existing regulatory frameworks may increasingly be interpreted in an AI-specific context (Electronic Arts, 2023h; Electronic Arts, 2024h; Electronic Arts, 2024j; Electronic Arts, 2025i).

Platform dependence can be understood as a specific sub-case within the broader category of regulatory risks. Electronic Arts states that it maintains strong relationships with its platform partners (Bloomberg Technology, 2021). However, given its reliance on major distribution platforms for console (Sony, Microsoft) and mobile (Apple, Google) markets, Electronic Arts consistently emphasizes the need to comply with platform-specific licensing agreements, policies, and guidelines (Electronic Arts, 2020f; Electronic Arts, 2021h; Electronic Arts, 2022h; Electronic Arts, 2024h; Electronic Arts, 2025g). These platform requirements, when combined with governmental regulation, can impose additional operational constraints on the company. However, across the reviewed materials, no explicit references link AI usage directly to platform-dependence risks.

Reputational and ethical risks exhibit a pattern similar to that observed for regulatory risks: they are present throughout the entire period under analysis but acquire a more explicit AI-related framing in the post-AI Spring period. Reputation and trust are consistently identified as key competitive factors in the industry in both pre- and post-AI Spring disclosures. Initially, these risks are discussed in relation to issues such as variable digital items in games (Electronic Arts, 2020f; Electronic Arts, 2022h) and ethical concerns related to excessive gameplay or gaming disorder (Electronic Arts, 2020f). In post-AI Spring materials, AI is increasingly incorporated into this discourse, with explicit acknowledgements that AI use may raise ethical concerns and could result in reputational harm if mismanaged (Electronic Arts, 2025g).

Overall, the evidence indicates that Electronic Arts explicitly recognizes regulatory, ethical, and reputational risks in relation to the application of AI, with a clear shift toward more explicit and formalized articulation of these risks in the post-AI Spring period.

### **3.3.2 Infrastructure and Data Challenge**

Electronic Arts consistently emphasizes technical infrastructure as a core component of its business operations. Infrastructure characteristics such as reliability, availability, and security are repeatedly identified as critical factors for overall business stability and growth (Electronic Arts, 2020f; Electronic Arts, 2020e; Electronic Arts, 2020g; Electronic Arts, 2021h; Electronic Arts, 2022h; Electronic Arts, 2021i; Electronic Arts, 2023h; Electronic Arts, 2024h). While company reports do not explicitly state that infrastructure limitations directly constrain AI adoption at

Electronic Arts, this relationship can be inferred, given the central role of infrastructure across all business activities.

Within the infrastructure domain, Electronic Arts identifies two primary concerns: the potential inability to scale infrastructure effectively in line with business needs (Electronic Arts, 2022h) and security-related risks. Security is consistently framed as an important competitive factor (Electronic Arts, 2020f; MIT TR Arabia, 2021), receives oversight at the board level (Electronic Arts, 2022i), and is supported through regular internal training programs (Electronic Arts, 2024i).

Cybersecurity is explicitly treated as a standalone risk across the entire period under analysis, with Electronic Arts repeatedly noting that the gaming industry is particularly exposed to cyber threats (Electronic Arts, 2020f; Electronic Arts, 2021h; Electronic Arts, 2023h). In the post-AI Spring period, artificial intelligence is introduced into this discourse in an unexpected manner: AI is framed not only as a technology to be protected, but also as a potential amplifier of cybersecurity threats. Company disclosures acknowledge that AI can be used to develop more sophisticated attack methods characterized by higher levels of automation and coordination (Electronic Arts, 2024h; Electronic Arts, 2024j; Electronic Arts, 2025g; Electronic Arts, 2025i). This represents a notable shift in framing, where AI is considered not only through a benefits-risks trade-off of its implementation, but also as a direct external threat to a specific dimension of Electronic Arts' operations. In the post-AI Spring period, Electronic Arts demonstrates concrete steps toward mitigating security-related risks by establishing a dedicated cross-functional team responsible for the approval and oversight of AI models (Electronic Arts, 2025h)

Data dependency is not explicitly articulated as a risk in the case study materials. However, it can reasonably be interpreted as such given the scale and centrality of data across multiple AI use cases. For example, certain machine learning algorithms rely on millions of frames of advanced match-capture data to generate animations (Electronic Arts, 2021b; Electronic Arts, 2021a). Data are also foundational for EA Sports franchises, where Electronic Arts has access to extensive datasets covering athletes, teams, stadiums, and leagues (Electronic Arts, 2021g). AI applications for NPC behaviour and gameplay systems similarly depend on real-world and telemetry data (Electronic Arts, 2024k; Electronic Arts, 2025j; Electronic Arts, 2025b). During earnings calls, Electronic Arts emphasizes that data lies at the centre of meaningful technological advancement (Electronic Arts, 2025d) and explicitly treats rich datasets as a key competitive advantage (Electronic Arts, 2024f).

In summary, technical infrastructure, infrastructure security, and the availability of sufficiently rich data emerge as foundational conditions for AI implementation at Electronic Arts.

Conversely, limitations or vulnerabilities in these areas function as important challenges that may constrain the successful adoption and scaling of AI-related practices. Overall, the perception of these risks remains largely stable across the entire period under analysis, and no substantial changes can be identified between the pre-AI Spring and post-AI Spring periods, except for the emerging perception of AI itself as a potential threat, as discussed above.

### **3.3.3 Talent and Skill Challenges**

As a knowledge-based business, the ability to attract and retain talent is treated by Electronic Arts as a key competitive factor (Electronic Arts, 2020f; Electronic Arts, 2021h; Electronic Arts, 2022h; Electronic Arts, 2023h; Electronic Arts, 2023c; Electronic Arts, 2024h; Electronic Arts, 2025g). The company also explicitly acknowledges that it is a target of aggressive employee solicitation, which may lead to increased employee compensation costs (Electronic Arts, 2021h). Similar to the case of technological infrastructure, Electronic Arts does not articulate talent and skills explicitly in an AI-specific context. However, it consistently emphasizes their fundamental importance for overall business performance, which implicitly extends to the implementation and scaling of AI-related practices.

### **3.3.4 AI-Specific Constraints**

The final group of challenges comprises AI-specific constraints. These challenges do not exhibit a coherent or systematic representation across the entire research period, and even in the post-AI Spring phase they appear only intermittently. When mentioned, they are framed exclusively in an AI-related context and are not linked to broader business areas.

One such constraint concerns the of AI model bias. This issue is first explicitly mentioned in 2021 (MIT TR Arabia, 2021). In the post-AI Spring period, bias-related risks reappear alongside references to mitigation efforts, particularly in the context of dedicated internal training initiatives aimed at responsible AI use (Electronic Arts, 2025h).

Another AI-specific constraint relates to the high costs and extended time requirements associated with AI model training. However, this issue is mentioned only briefly and primarily at the level of EA-affiliated research, rather than in managerial or strategic disclosures (Gillberg et al., 2023).

A further dimension of AI-specific constraints concerns the limited computational capacity of gaming devices. Since 2020, Electronic Arts has repeatedly emphasized that increased

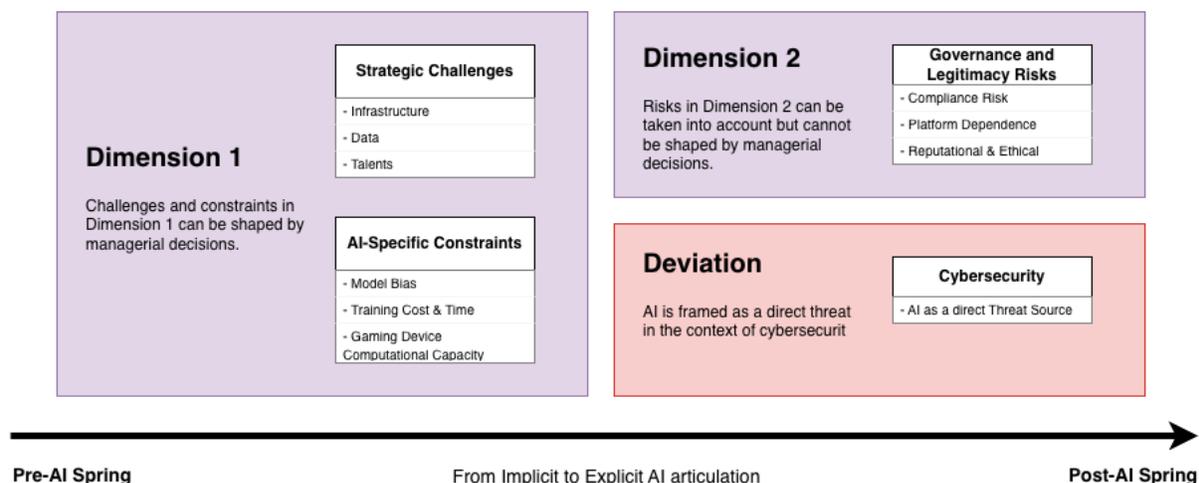
hardware performance expands technological possibilities in games (Electronic Arts, 2020a; Electronic Arts, 2021c; Electronic Arts, 2021d). In this context, EA SEED’s General Manager explicitly notes that heterogeneity in device power limits the broad adoption of more advanced AI solutions across the player base (MIT TR Arabia, 2021).

In summary, this category captures a set of challenges that are specific to AI technologies, including model bias, the cost and duration of AI training, and limitations imposed by player hardware. While these challenges are not consistently articulated across the case study materials, they are nevertheless present (particularly in the pre-AI Spring period) indicating an early awareness of AI-specific constraints within Electronic Arts.

### 3.3.5 Synthesis of AI Adoption Risks and Challenges

Based on the findings presented in Sections 3.3.1-3.3.4, we synthesize a model with AI Risks and Challenges in Electronic Arts. The model is presented in **Figure 8**.

**Figure 8.** AI Risks and Challenges in Electronic Arts



*Source:* Prepared by the author based on case study materials

The model distinguishes between two overarching dimensions of risk. Both Dimension 1 and Dimension 2 affect core business conditions across Electronic Arts’ operations.

The first dimension comprises strategic challenges and AI-specific constraints, which can be shaped through managerial decisions. Strategic challenges are rarely explicitly labelled by the company as “AI risks” or “AI challenges”; however, they function as implicit or silent constraints

on AI adoption and scaling. These challenges correspond to key elements of AI readiness and include infrastructure, data, and talent capabilities. They therefore need to be addressed at the strategic level.

AI-specific constraints include model bias, the cost and duration of AI model training, and limitations imposed by gaming hardware capabilities. These challenges are articulated less consistently and appear primarily in technical keynotes or EA-affiliated research papers rather than in formal corporate disclosures. Importantly, this dimension does not constitute a strategic level of risk. The identified constraints are largely solvable at the technical or operational level and do not require direct strategic or executive involvement.

Dimension 2 captures governance and legitimacy risks, which can be taken into account by the company but cannot be shaped through managerial decisions. In the pre-AI Spring period, governance and legitimacy risks were framed in general regulatory and compliance terms. In the post-AI Spring period, however, these same risks increasingly receive explicit AI-related articulation, indicating an emerging trend toward the formal recognition of AI-specific implications within broader governance structures.

Cybersecurity represents a notable deviation from the dominant AI risk framing. In this context, AI is not positioned within a conventional risk-benefit logic of adoption but is explicitly described as a direct source of threat, due to its potential to enable more sophisticated and automated cyberattacks.

Overall, the model systematises the key risks and challenges associated with AI adoption at Electronic Arts, highlighting their different scopes, levels of articulation, and implications for managerial action

### **3.4 Entrepreneurial Strategies for AI adoption**

In Section 3.3, we address RQ3 by examining the strategic decisions that support and favour AI adoption. Using Electronic Arts as a case example, we identify and analyse three groups of strategic decisions reflected in the case study materials: Strategic Recognition of AI at the Executive Level, Structuring AI Applications Around Strategic Focus Areas, and AI Capability Building.

#### **3.4.1. Strategic Recognition of AI at the Executive Level**

A key prerequisite for successful AI adoption is the recognition of its strategic importance at the highest level of the organisation. The case study materials indicate that while top management has retrospectively framed AI as being relevant to Electronic Arts throughout the company's history, explicit and formalized statements regarding AI's strategic role emerge only in the post-AI Spring period.

During earnings calls in 2024, for example, senior executives emphasized that AI has been deeply embedded in Electronic Arts' products since the company's inception and positioned it as central to the functioning of its games (Electronic Arts, 2024f). From 2024 onward, AI is also increasingly articulated as a distinct strategic priority by the company's highest governance bodies. The Board of Directors is reported to exercise regular oversight over AI-related activities, particularly with respect to the implementation of generative AI (Electronic Arts, 2025i) and the role of generative AI within broader corporate strategy (Electronic Arts, 2024i). It is worth noting that toward the end of the post-AI Spring period, a dedicated director was appointed to oversee AI-related technologies (Electronic Arts, 2025i).

In a similar direction, artificial intelligence (together with governance and sustainability) is explicitly identified as a priority area for shareholders (Electronic Arts, 2025i).

This heightened strategic attention from senior stakeholders is further institutionalized through formal performance management mechanisms. According to the 2025 Proxy Statement, AI-related business objectives were incorporated into the key performance indicators used to evaluate top management performance, with a specific focus on the development and execution of the company's generative AI strategy (**Table 3**)

**Table 3. Business Performance of Electronic Arts (excerpt)**

	Business Objectives	Key Measures	Key Highlights and Results
10%	Artificial Intelligence Build out and execute against a GenAI strategy that centres around efficiency, expansion and transformation	<ul style="list-style-type: none"> <li>• Advance taskforce on strategy and goals and adopt governance structure; and identify multi-year success metrics</li> <li>• Define plan including multi-year roadmap with key milestones and deliverables; meet FY25 deliverables</li> </ul>	<ul style="list-style-type: none"> <li>• Achieved via taskforce that prioritized focus areas/goals and by adopting a governance structure to support go-forward initiatives, as well as by identifying success metrics</li> <li>• Substantially completed applicable milestones, with all delivered in FY25 and one to be delivered in early FY26</li> </ul>

*Source:* Electronic Arts, 2025i

In summary, the findings suggest that the level of attention devoted to AI by key stakeholders is closely aligned with the intensity of its integration into the company's processes. This pattern is referred to in this study as "Strategic Recognition".

### 3.4.2. Structuring AI Applications Around Strategic Focus Areas

As shown in Section 3.2, AI applications at Electronic Arts are not distributed evenly across the game's lifecycle. Instead, the empirical material supports an interpretation that Electronic Arts structures its AI applications primarily around specific strategic focus areas.

One illustrative example is the company's emphasis on creating safe player environments, ensuring fair play, and preventing fraud. These priorities are consistently articulated in EA's company reports and earnings calls (Electronic Arts, 2020g; Electronic Arts, 2020b). Correspondingly, Electronic Arts undertakes a range of activities to support this focus area, including the deployment of tools and technologies (Electronic Arts, 2020g; Electronic Arts, 2022h), the simplification of reporting and feedback mechanisms (Electronic Arts, 2021i), investments in resources aimed at deterring unfair behaviour (Electronic Arts, 2021i; Electronic Arts, 2024i), and initiatives designed to limit the impact of abuse (Electronic Arts, 2021h;

Electronic Arts, 2022h). In line with this strategic focus, AI applications are also concentrated in this area, particularly among AI use cases associated with the game delivery stage.

A similar, but more fully developed pattern can be observed with respect to acceleration and production efficiency. Electronic Arts explicitly identifies accelerated content generation as a strategic priority (Electronic Arts, 2024h), alongside the ability to iterate more rapidly during development (Rapid Response, 2024). At the same time, production efficiency is consistently framed as a key benefit of AI adoption. In the post-AI Spring period, this alignment becomes operationalized through the more active use of AI in asset creation, where AI technologies are applied specifically to reduce development time and accelerate production workflows. In this case, the alignment can be traced across three levels: strategic focus → perceived AI benefit → concrete AI application.

However, not all strategic focus areas fully close this alignment loop. For example, Electronic Arts frequently emphasizes its focus on delivering new experiences (Electronic Arts, 2022h) and simultaneously frames the creation of new experiences as a core benefit of AI, as discussed in Section 3.2.4. Despite this, clearly articulated AI use cases explicitly linked to the creation of new experiences are limited or absent in the analysed materials. A similar pattern can be observed for other declared priorities, such as socially connected ecosystems and creative community ecosystems. While these areas are repeatedly identified as major strategic focuses in the post-AI Spring period (Electronic Arts, 2023f; Electronic Arts, 2023h; Electronic Arts, 2024h; Electronic Arts, 2024e), corresponding AI applications are not yet clearly observable.

In summary, the findings indicate a partial but consistent correlation between Electronic Arts' strategic focus areas and the distribution of AI applications. While this alignment is not universal across all declared priorities, it nevertheless represents an identifiable element of the company's approach to AI adoption. This strategic pattern is conceptualized here as "Structuring Around Strategic Areas".

### **3.4.3. AI-Capability Building**

Capability building constitutes an important element of strategic AI adoption at Electronic Arts. The empirical material suggests three main directions of capability building within the company: technical capability building, talent capability building, and data capability building.

Technical capability building encompasses the development of technical infrastructure and sustained investments in R&D. Evidence of technical capability building can be observed throughout the entire period under analysis. However, it acquires a more explicit AI-related

framing in the post-AI Spring period. In the pre-AI Spring period, case study materials indicate that Electronic Arts made systematic investments in R&D as part of its general innovation activities (Electronic Arts, 2020a; Electronic Arts, 2021d). In the post-AI Spring period, similar references to broad R&D investment continue to appear (Electronic Arts, 2024h) but are increasingly complemented by explicit references to AI-focused R&D initiatives (Electronic Arts, 2023h; Electronic Arts, 2023c; Electronic Arts, 2025i). This shift suggests the emergence of a distinct AI-related R&D dimension that becomes integrated into the company's broader AI implementation strategy.

Talent capability building includes the acquisition, retention, and training of highly qualified employees. Human capital is consistently treated as a critical factor by Electronic Arts in both the pre-AI Spring and post-AI Spring periods (Electronic Arts, 2020c; Electronic Arts, 2023f). Over time, the company reports a range of initiatives aimed at motivating and retaining employees, including stock-based compensation (Electronic Arts, 2020f; Electronic Arts, 2021j), wellness programs (Electronic Arts, 2021h), and other incentive and bonus schemes (Electronic Arts, 2024j). The materials also indicate the existence of structured training activities and internal learning resources already in the pre-AI Spring period (Electronic Arts, 2020g). In the post-AI Spring period, AI-specific training initiatives begin to emerge more clearly (Electronic Arts, 2024i). At the senior management level, talent acquisition is also used to strengthen AI-related competencies, including the recruitment of senior executives with cloud and AI expertise from external technology firms (Electronic Arts, 2022f). Overall, talent acquisition, retention, and training practices appear broadly consistent across both periods, with a notable increase in attention to AI-specific skill development after the AI Spring.

Data capability building refers to activities related to the systematic collection, management, and utilization of data required for AI systems. Although the case study materials do not explicitly describe dedicated data capability-building initiatives, Electronic Arts can be characterized as possessing an advanced level of data capability. The company repeatedly emphasizes the scale and historical depth of its datasets (more than 40 years of data) as a key competitive advantage (Electronic Arts, 2024f), which implicitly underpins its AI-related activities.

In summary, the development of technical, talent, and data capabilities was already present at Electronic Arts in the pre-AI Spring period, but these capabilities increasingly became embedded within an explicit AI context in the post-AI Spring period. This evolution constitutes a distinct strategic element of AI adoption at Electronic Arts, conceptualized here as "AI Capability Building."

### 3.4.5. Synthesis of AI Adoption

Based on the findings presented in Sections 3.4.1-3.4.3, we synthesize Entrepreneurial Strategies in Electronic Arts (**Table 4**).

**Table 4.** *Entrepreneurial Strategies in Electronic Arts*

Strategy Name	Role
Strategic Recognition	Legitimizes and drives AI adoption by framing AI as a strategic priority embedded in executive objectives and governance structures.
Strategic Alignment	Directs AI initiatives into existing strategic focus areas, leading to selective and non-uniform adoption aligned with perceived benefits.
Capability Building	Enables the development, scaling, and value creation of AI applications through infrastructure, data, and talent capabilities.

*Source:* Prepared by the author based on case study materials

The table illustrates three core elements of AI adoption strategies at Electronic Arts.

Strategic Recognition functions as the legitimizing and driving force behind AI adoption within the company. It aligns the organisation toward AI implementation through the formal inclusion of AI-related objectives in executive key performance indicators and the establishment of Board-level oversight. In doing so, strategic recognition signals to organisational actors that AI constitutes a component of the company's strategic orientation, corporate identity, and future value creation. In the pre-AI Spring period, Strategic Recognition in relation to AI was largely implicit. In contrast, in the post-AI Spring period this strategic push becomes more explicit and gains renewed momentum.

While strategic recognition provides the initial push for AI adoption, Structuring Around Strategic Areas determines how AI use cases are subsequently distributed across the organisation. Once initiated by this strategic push, AI initiatives tend to emerge within the company's pre-existing strategic focus areas, guided by the perceived benefits of AI. As a result,

AI applications are not adopted uniformly or randomly but instead become selectively concentrated in domains that align with established strategic priorities.

Following this alignment, the successful development and scaling of AI applications depend on AI Capability Building, encompassing technological infrastructure, talent and skills, and data capabilities. The availability and quality of these capabilities influence the extent to which AI applications (initiated through strategic recognition and positioned within specific strategic areas) can mature, scale, and generate tangible value for the company.

Overall, the model systematises the key elements underlying AI adoption strategies at Electronic Arts and clarifies how strategic intent, prioritization mechanisms, and organisational capabilities jointly shape the outcomes of AI implementation.

### **3.5 Integration of findings in a model and comparison with the AISF framework**

In Section 3.5, we integrate the empirical findings related to **RQ1-RQ3** into a single explanatory model and compare this model with the AISF developed in the theoretical part of the thesis. In addition, we assess the empirical findings against the hypotheses formulated in Section 1.3.2.

#### **3.5.1. AI implementation model for Electronic Arts**

Following the analysis of (i) AI applications at Electronic Arts (RQ1), (ii) the associated risks and challenges of AI adoption (RQ2), and (iii) entrepreneurial strategies that favour AI adoption (RQ3), we integrate our findings into a single AI Implementation Model for Electronic Arts. The model is presented in **Figure 9**.

The model is organised around AI adoption as the core construct and consists of three analytical layers: Strategic, Adoption, and Outcome. The model is also supported by a temporal dimension that captures shifts in AI articulation in pre-AI Spring vs post-AI Spring periods.

The Strategic Layer comprises the AI adoption strategies discussed in Section 3.4, namely Strategic Recognition, AI Capability Building, and Structuring Around Strategic Focus Areas.

The Adoption Layer includes the risks and challenges of AI adoption discussed in Section 3.3, as well as the perceived AI benefits identified in Section 3.2.4.

The Application Layer captures the AI applications discussed in Section 3.2, structured around the three stages of the game lifecycle: Game Creation, Game Delivery, and Runtime/Play.

At the bottom of the model, a temporal layer illustrates the shift in AI articulation from implicit in the pre-AI Spring period to more explicit in the post-AI Spring period.

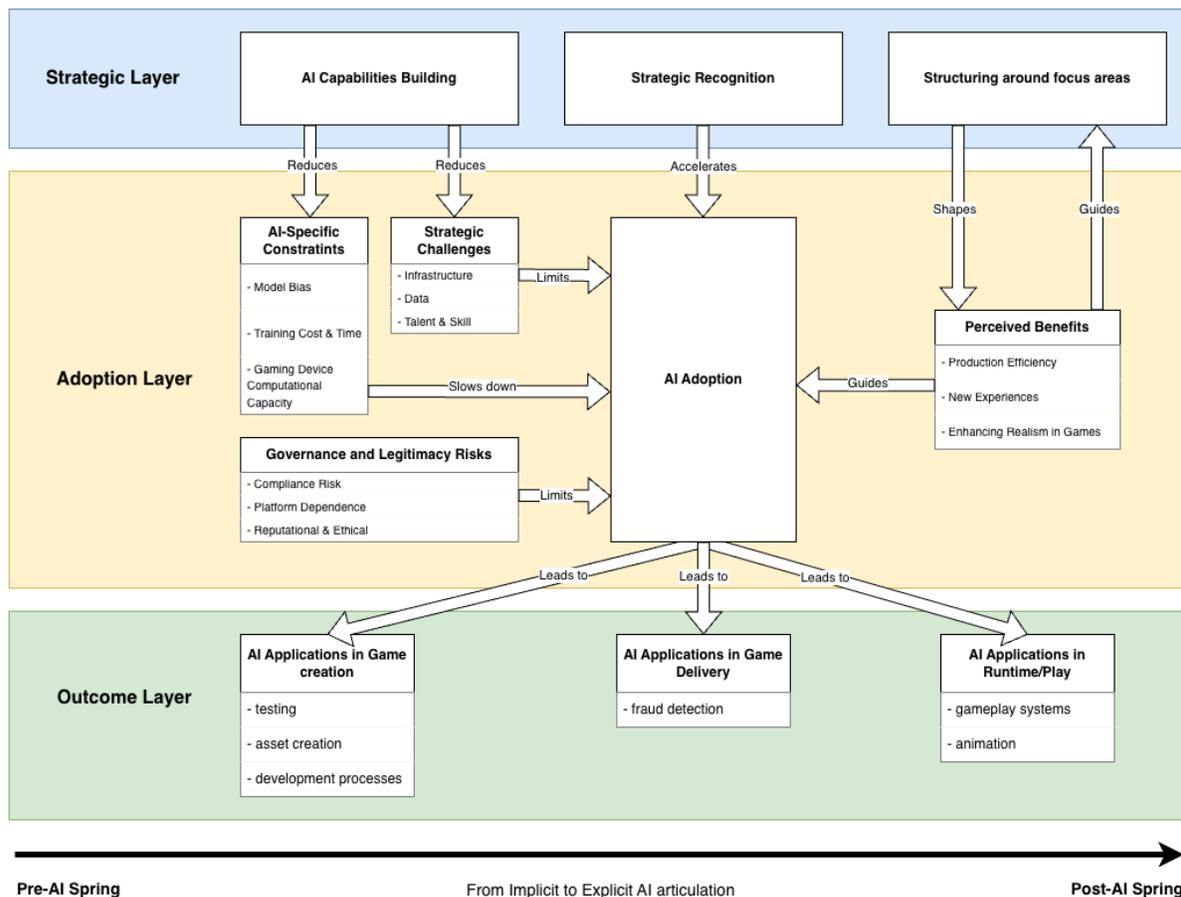
The Strategic Layer influences the Adoption Layer through several mechanisms. Strategic Recognition accelerates AI adoption by legitimizing AI at the organisational level and embedding it into governance and performance structures. AI Capability Building reduces both strategic challenges (such as infrastructure, data, and talent constraints) and AI-specific constraints (including model bias, training cost and duration, and computational limitations of gaming devices). With respect to gaming hardware, it is important to note that Electronic Arts does not manufacture gaming consoles; therefore, this influence concerns not device power itself, but the extent to which AI technologies can be effectively deployed on existing hardware. Finally, Structuring Around Strategic Focus Areas shapes how AI benefits (production efficiency, new experiences, and enhanced realism) are perceived and prioritized, while simultaneously being guided by these perceived benefits.

Within the Adoption Layer, strategic challenges and AI-specific constraints influence the pace and scope of AI adoption. Strategic challenges represent fundamental limitations that can restrict AI adoption. AI-specific constraints, by contrast, are primarily tactical or technical in nature and do not prevent AI adoption but rather slow its progression. Governance and legitimacy risks (including compliance requirements, platform dependence, and reputational and ethical risks) are also represented at this layer. These risks are largely external and cannot be directly altered by the company's strategic actions; instead, they must be accounted for in AI adoption decisions, thereby acting as additional limiting factors. On the opposite side of the Adoption Layer, perceived AI benefits guide adoption priorities: benefits that are more visible or strategically prioritized tend to attract AI adoption earlier than others. The interaction between perceived benefits and adoption constraints ultimately leads to concrete AI implementations at the Application Layer.

The Application Layer reveals an uneven distribution of AI applications across the game lifecycle. The Game Creation stage includes AI applications in testing, asset creation, and development processes, while the Runtime/Play stage includes gameplay systems and in-game animation. These two stages show the highest concentration of AI use cases. In contrast, the Game Delivery stage exhibits a lower concentration of AI applications.

Finally, the temporal dimension of the model highlights differences between the pre-AI Spring and post-AI Spring periods. In the pre-AI Spring period, AI is largely articulated implicitly by company management. In the post-AI Spring period, AI receives more explicit and formalized attention. This shift is also accompanied by the emergence of generative AI as a distinct and increasingly visible sub-category of AI within Electronic Arts.

**Figure 9. AI Implementation Model for Electronic Arts**



*Source:* Prepared by the author based on case study materials

Overall, the model illustrates the structure of AI implementation at Electronic Arts by integrating entrepreneurial strategy, the management of risks and benefits, and their interactions across organisational layers. It demonstrates how these dynamics collectively shape the emergence and distribution of AI applications within the company.

### 3.5.2. Comparison with the AI Strategy Framework

The EA AI Implementation Model can be interpreted as a firm-level specification of the AISF constructs. While the AISF is a general model explaining how AI implementation is carried out in game studios, the EA AI Implementation Model puts this logic into a concrete context of how strategic actions, challenges, risks, constraints, and perceived benefits interact and lead to a specific set of realized AI practices in a large game company.

In the AISF, the APS represents the full set of AI applications that are technologically possible in the gaming industry at a given time. The AFS represents the subset that appears realistic for a specific studio, after it is filtered by AI readiness, AI benefits, and AI risks. The EA AI Implementation Model does not try to map the entire APS in the abstract, but by integrating the concept of the AI Spring and the pre-AI Spring and post-AI Spring periods, it implicitly indicates that the APS was expanded by a new technology at a given moment. Then it starts from the empirically observed AI applications (Application layer) and explains why this set of practices emerged within EA. In this mapping, the Application layer corresponds most directly to the AIS in the AISF, while the Adoption layer is somewhat similar to the EA's AFS by specifying the concrete risks-benefits configuration that shapes feasibility inside EA.

The Strategic layer of the EA model corresponds to the main factors that, in the AISF, influence feasibility and implementation (AI readiness and AI deployment). The AISF argues that AI readiness (TOE conditions and dynamic capabilities) influences whether industry-level possibilities can become realistic opportunities for a firm. In the EA model, AI readiness is expressed through AI Capability Building, which captures infrastructure, talent, and data as resources that expand feasibility by reducing challenges and constraints. The AISF also notes that feasible opportunities do not automatically become realized practices. Instead, firms need deployment practices that help convert the AFS into the AIS. In the EA model, this conversion is not described explicitly (e.g., Agile/Lean), but there are implicit indications of it, for example, through the Strategic layer. Strategic Recognition increases organisational commitment by legitimizing AI, while Structuring Around Strategic Areas shapes adoption into domains where perceived benefits are highest and implementation is more workable for the organisation.

A key refinement that the EA model adds to the AISF is the level of detail in feasibility constraints. The AISF treats feasibility as shaped by readiness, benefits, and risks. The EA model decomposes this into different categories. In particular, it distinguishes constraints that limit adoption (strategic challenges and governance/legitimacy risks) from constraints that primarily slow down adoption (AI-specific constraints). This distinction is especially relevant in gaming contexts, where computational feasibility depends partly on player devices, which affects whether advanced AI features can be deployed consistently across the player base.

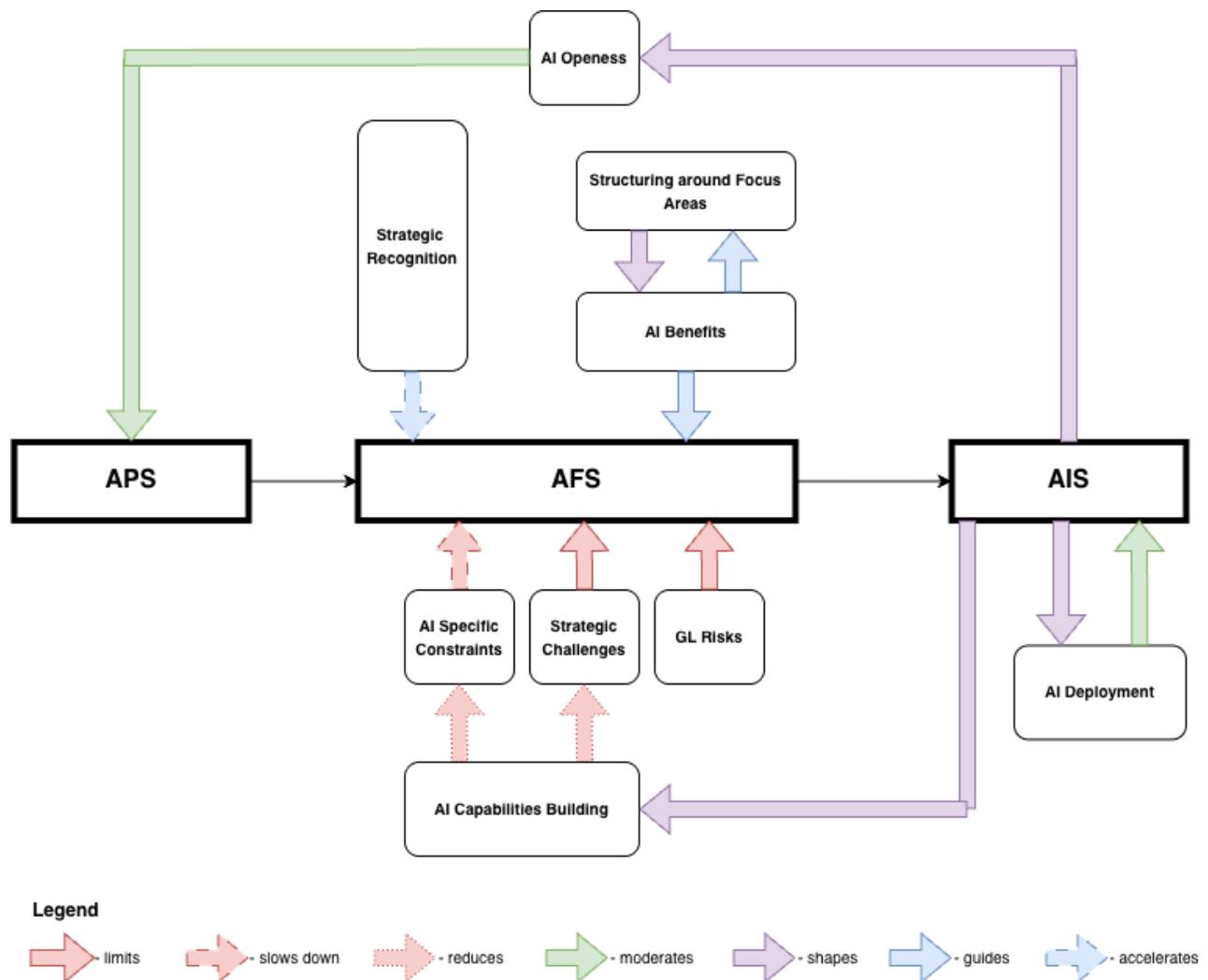
At the same time, the EA model is narrower than the AISF in terms of explicit feedback loops and industry-level effects. The AISF highlights that realized practices (AIS) can feed back into readiness, deployment routines, and perceptions of risks and benefits, and that firm-level innovation can also expand the industry's APS through diffusion. In the EA model, feedback is not represented properly, except for the relationship between perceived benefits and structuring

around strategic areas, which indicates that perceived value both shapes and is shaped by strategic prioritization over time. In addition, the temporal shift from implicit to explicit AI articulation can be interpreted as an indirect sign of feedback: as AI becomes more visible in the post-AI Spring period, it is embedded more explicitly into corporate strategy.

Overall, the AISF retains a broader scope, while the EA model provides a more detailed internal logic of adoption and distribution within one firm. We

To make the AISF fit the EA AI Implementation Model better, several adjustments can be made which we visualized in **Figure 10**.

**Figure 10.** AI Strategy Framework (EA amended)



Source: Prepared by the author based on case study materials

First of all, the AISF should show strategy as its own “step,” not only as a background condition. In the EA case, top management does not just “have readiness” or “do deployment.” It also actively accelerates AI (Strategic Recognition) by embedding AI into priorities and KPIs, which clearly speeds up adoption. In addition, EA’s adoption is shaped by how the company chooses focus areas: certain advantages of AI (efficiency, new experiences, realism) become “real” adoption drivers only when they are translated into strategic benefits. So, the AISF should be adjusted by adding explicit elements such as Strategic Recognition + Strategic Focus, which accelerate and guide the AFS accordingly. This makes it clearer why some AI use cases move faster than others inside a large firm.

Second, the AISF should divide AI risks into three types, because they work differently in the EA AI Implementation Model. If the AISF keeps “AI risks” as one broad box, it becomes harder to explain why firms may still adopt AI but only in certain areas, or why adoption progresses unevenly across the lifecycle. AI Capability Building, which reduces AI-specific constraints and strategic challenges, also should be added.

### **3.5.3 Reflection on the hypotheses**

The reflections below identify where the EA findings align with our hypotheses presented in section 1.3.2.

**H1** proposes that game companies should use AI exploration practices to broaden their AFS. In the EA case, the evidence is consistent with this logic: capability-building activities (e.g., infrastructure, talent, and data-related efforts) appear as important conditions for expanding what EA can realistically pursue with AI. At the same time, the case also indicates that feasibility expansion is not evenly reflected across all strategic areas. Some priorities are clearly communicated, but not all of them are equally visible in terms of AI applications. This implies that the AFS broadening may be uneven across domains, or that some exploration remains less observable externally.

**H2** proposes that game companies should use AI deployment practices to achieve a higher conversion rate from the AFS to the AIS. Since the case study does not measure “conversion rates,” the hypothesis is assessed indirectly. The EA model provides support for the underlying idea: once AI becomes strategically recognized and linked to corporate priorities, AI initiatives appear more likely to move from feasibility to implementation. However, the case also suggests that implementation remains selective and uneven across the game lifecycle. This indicates that even when AI is feasible, not all feasible opportunities are implemented at the same

speed or scale, likely because feasibility is shaped by constraints, risk considerations, and strategic focus.

**H3** proposes that game companies should reach a minimum threshold of AI strategic baseline to launch the AISF (AI readiness, AI Deployment competences, perception of AI Benefits, and perception of AI Risks). EA appears to have some pre-existing capabilities and AI-related practices before the AI Spring. After the AI Spring these become more explicitly framed and institutionalized. In other words, EA had a certain threshold during the entire research period which allowed it to implement AI.

**H4** proposes that game companies should ensure that AIS feed knowledge back to AI strategic baseline to ensure that the AISF loop becomes self-reinforcing and evolves over time. The EA case offers partial support for this hypothesis at the level that can be observed externally. There are indications that perceived benefits and strategic priorities influence each other over time, and that AI becomes increasingly embedded in formal strategic language after the AI Spring. However, because internal learning cycles are not directly observable in public sources, the case cannot fully demonstrate how specific implementations reshape internal routines, decision processes, or capability-building in detail. Therefore, H4 is supported mainly through changes in strategic articulation and formalization, rather than through direct evidence of internal feedback mechanisms.

## CONCLUSIONS AND RECOMMENDATIONS

### (a) Conclusions

1. **AI adoption practices in B2C game companies can be categorised along the game lifecycle.** Our research shows that AI applications can be found across game creation, game delivery, and runtime/play, but are not distributed evenly. In Electronic Arts, the most evidenced AI applications concentrate in game creation (testing and assets creation) and runtime/play (gameplay systems, NPC, and animation), while game delivery AI applications are present in a smaller manner (or less explicitly documented and articulated).
2. **Successful AI adoption depends on “readiness” conditions within game companies and externally shaped governance risks.** Our research indicates that AI adoption is enabled and limited by foundational organisational conditions: technical infrastructure, data, and talent capabilities. Alongside these internal conditions, AI adoption is shaped by governance and legitimacy issues that organisations can take into account but cannot fully control (e.g., regulations, ethical, and reputational issues). In addition, AI appears in the case not only as an adopted capability but also as a factor that can intensify certain threats (cybersecurity).
3. **Strategies that favour AI adoption extend beyond “having and developing AI capabilities” but include explicit strategic recognition.** Our research suggests that AI adoption is accelerated when top management formalises AI as a strategic priority and embeds it into executive performance logic. In parallel, AI initiatives appear more actionable when they are directed into already prioritised strategic areas, rather than being left as isolated technology experiments. Capability building is important. However, capability building alone cannot explain adoption pace and internal diffusion without accompanying strategic recognition and prioritisation.
4. **The AISF offers an explanatory structure that connects industry possibilities to firm-level implementation outcomes, while the case refines how feasibility constraints should be specified.** The thesis achieves its central objective by developing an analytical framework that links (i) the industry-level AI possibility space, (ii) a firm’s AI feasibility space shaped by challenges/risk, benefits, and strategy, and (iii) a firm’s AI implementation space, which is moderated by deployment practices. Our case study supports the general logic of the framework. It also indicates that AI risks are more analytically useful when they are divided into strategic challenges, AI-related constraints, and governance risks. Beyond existing frameworks, the AISF conceptualise AI adoption not as a single one-time action, but as a looped cycle that combines various technology adoption elements into a single structure.

5. **The “AI Spring” functions as a point that changes perception of AI-labelled technologies.** Post-AI Spring period demonstrates both the increased availability of AI technologies (including GenAI) and a change in company's AI-related communications. In post-AI spring period AI is discussed more explicitly, more frequently, and more formally. This shows that AI influences entrepreneurial strategy not only by improving tools and processes, but also by changing how firms understand new opportunities, decide what to prioritise, and justify where to invest resources.
6. **Our conclusions are analytically grounded but should be generalised with caution due to design-related limitations.** Our research implements a single-case research method and public sources as a data source. This approach supports theory development and pattern identification but limits strong generalization across firm types. Therefore, our research is therefore most reliable as a structured explanation of how AI adoption may co-evolve in a large B2C game company. We also believe that it can guide further research in different contexts.

#### (b) Recommendations

Theoretical recommendations and directions for further research

1. **Multiple-case study is recommended to test the AISF.** For example, Future research may involve multiple-case study or comparative case study across various firm sizes (AAA publishers, mid-sized studios, startups), geographies, and business models (free-to-play, premium, mixed). It can be useful to identify which elements of the framework remain stable and which are shaped by firm type.
2. **Greater access to internal decision-making data would strengthen explanatory power.** Studies that combine public materials with internal interviews, project documentation, or ethnographic access may clarify mechanisms that are only weakly observable externally. In particular, it would allow for a clearer identification of the conversion of feasible AI opportunities into implemented AI practices.
3. **Defining and measuring key constructs would make it possible to test the framework using quantitative or mixed methods.** Future research could develop concrete indicators for concepts such as the breadth of the feasibility space, the strength of shaping factors (e.g., challenges, risks, and strategic decisions), and the extent to which feasible AI opportunities are actually implemented. This would enable hypothesis testing and comparisons across companies.

#### Practical recommendations

1. **It is advisable to treat AI strategy as a management topic, not only as a technology initiative.** Organisations may benefit from setting up a cross-functional group involving functions such as product, engineering, legal, security, and HR to coordinate AI-related activities. This group can define priorities, oversee progress, and ensure that AI initiatives remain aligned with overall business strategy and organisational responsibilities.
2. **AI activities should be prioritised based on their strategic relevance and expected benefits.** When choosing use cases, managers may consider the type of value AI is expected to deliver, how feasible implementation is given existing resources and systems, and the level of governance or reputational risk involved. This approach creates a balanced portfolio of AI applications rather than isolated experiments.
3. **Investment in basic AI readiness remains essential for AI implementations and its scaling.** Companies may benefit from prioritising data quality, secure computing infrastructure, and reliable processes for developing and maintaining AI systems. At the same time, targeted training and selective hiring can help spread AI knowledge across the organisation and reduce reliance on a small group of specialists.
4. **A human - AI interaction rather than full automation is recommended as a more reliable design principle for development and business workflows.** In practice, organisations may gain more consistent value when in production workflows AI tools are positioned as accelerators for idea generation, iterations, and development. In this case human review should remain for style coherence and risk detection.

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## ANNEXES

### Annex 1

#### **Case study protocol**

*Source:* Prepared by the author based on Yin (2018)

#### **Section A. Overview Of The Case Study**

##### 1. Mission and Goals

The mission of this case study is to examine how artificial intelligence (AI) shapes entrepreneurial strategies in the gaming industry, using Electronic Arts (EA) as the primary case.

The study adopts a temporal comparative lens centred around the AI Spring (Nov-Dec 2022) - a structural shock that expanded the APS and likely initiated a new iteration of the APS - AFS - AIS cycle described in the AI Strategy Framework (AISF).

##### 2. Case Study Questions, Hypotheses, and Propositions

Main Research Question:

- How does AI shape entrepreneurial strategies in the gaming industry?

Supporting Questions:

- RQ1: What AI practices can game companies integrate into business and product strategy?
- RQ2: What challenges constrain AI adoption, and how are they addressed?
- RQ3: What strategic decisions favour better AI adoption?

Hypotheses:

- H1: Game companies should use AI exploration practices to broaden their AFS.
- H2: Game companies should use AI deployment practices to achieve a higher conversion rate from the AFS to the AIS.
- H3: Game companies should reach a minimum threshold of AI strategic baseline to launch the AISF: AI readiness, AI Deployment competences, perception of AI Benefits, and perception of AI Risks.

- H4: Game companies should ensure that the AIS feed knowledge back to AI strategic baseline to ensure that the AISF loop becomes self-reinforcing and evolves over time.

The case draws on the AISF. It integrates AI use cases across the game lifecycle with readiness factors, integration processes, decision-making theories, and ecosystem strategies.

#### 4. Role of the Protocol

This protocol ensures reliability and consistency in data collection, temporal coding, triangulation, and AISF-aligned analysis.

### **Section B. Data Collection Procedures**

#### 1. Contact Persons

No internal EA contacts available. All data are collected from public sources.

#### 2. Data Collection Plan

Sources of Evidence:

- Documentation (Annual Reports, 10-Ks, EA blogs, strategy documents)
- Direct observation (GDC talks, developer diaries)
- Published interviews (media, podcasts)
- Research papers of EA-affiliated researchers
- Other

Temporal Coding Requirement - Every evidence item is marked as:

- PRE-SPRING ( $\leq$  Nov 30, 2022)
- POST-SPRING ( $\geq$  Nov 30, 2022)

#### 3. Preparation

- Build a case study database with temporal and AISF coding fields.
- Identify EA's AI practices in creation, delivery, and runtime.
- Construct an initial APS/AFS/AIS baseline for 2020-2025.

## Section C. Protocol Questions

Guiding questions for the researcher.

1. How exactly did EA use AI in each domain (creation, delivery, runtime) before vs. after the AI Spring?

- Which specific AI tools, models, or workflows were used before the AI Spring?
- Which new generative or advanced AI capabilities appeared after the AI Spring?

2. How specifically did the AI Spring expand EA's strategic opportunities (APS)?

- Which new categories of AI use cases became possible only after the AI Spring?
- Did EA begin exploring opportunities that were not feasible earlier?
- Which previously impossible AI ideas became possible?

3. How did EA's feasibility conditions evolve from the pre-AI Spring phase to the post-AI Spring phase?

- Did EA recruit new AI-specialized talent or reorganise teams?
- Did infrastructure or data pipelines change?
- Did risk perceptions, constraints, or readiness indicators shift after the AI Spring?

4. How did EA's actual AI implementation decisions change after the AI Spring?

- Which AI projects were accelerated, expanded, cancelled, or newly launched?
- Did EA deploy AI into production in ways not observed before the AI Spring?
- Did implementation shift from experimentation to scaling, or vice versa?

5. How did EA's decision-making processes specifically change between phases?

## Section D. Tentative Outline For The Case Study Report

1. Audiences

Academic audience, researchers in AI/strategy, industry practitioners.

2. Outline

- Overview of EA
- AI practices of EA
- Constraints, Risks and Challenges of EA
- EA's Strategies for AI adoption
  - Integration of findings

## Annex 2

**Naming convention for case study materials**

## 1. Format:

- [CASE]\_[YYYYMMDD]\_[PHASE]\_[EVIDENCE TYPE]\_[SHORT TITLE]

## 2. Components:

- CASE - EA
- YYYYMMDD - Exact publication date for chronological and temporal analysis
- PHASE - PRE ( $\leq$  2022-11-30) or POST ( $\geq$  2022-12-01)
- EVIDENCE TYPE -
  - DOC (Documentation)
  - INT (Public Interview)
  - KEY (Keynote)
- SHORT TITLE - 3-6 words summarizing the content

## 3. Example:

- EA\_20230310\_POST\_DOC\_Impact Report FY2025

## Annex 3

## Codebook

Accelerated Content Generation is a focus	Competition for Talents
AI as a Scaling Tool	Consolidation in Gaming Industry (trend)
AI as Accelerator for Player Connection	Context: Apex Legends (Key IP)
AI as Creativity Accelerator	Context: Distributed Workforce
AI can be used for Localization	Context: FIFA-Ultimate Team (Key IP)
AI can be used for User Generated Content	Cost Optimization is Focus
AI for Asset Creation	Creative Ecosystems for Community is a focus
AI for Bringing New Experiences	Creativity important
AI for Business processes	Data as Advantage
AI for Development Processes	Data Dependence
AI for Dynamic Difficulty Adjustment	Data Privacy Risks
AI for Expansion of Offerings	Dedicated team for AI
AI for Fraud Detection	Development Delay/Cost
AI for Game Navigation	Distributed Development Model
AI for Gameplay System	Distribution Platform Dependency Risks
AI for In-Game Animation	EA as an Industry Leader
AI for Live Services	Ethical Risks
AI for Narrative Experiences	External initiatives
AI for NPC	External Partners
AI for Personalisation	Fail to Scale Infrastructure
AI for Production Efficiency	Fair play is a focus
AI for Production Workflows	Fraud Detection is a focus
AI for Recommendation Systems	Fraudulent activities are negative for business
AI for Rendering Techniques	Generative AI is at its early stage
AI for Safe Environments for Players	Good Relationships with Partners
AI for Sentiment Analysis	High costs of AI
AI for Testing	In-Company Consolidation of Services
AI is a formal business objective	Increase in Digital Distribution
AI is at scale	Increase in Digital Interaction
AI is important for Board	Infrastructure Dependence
AI is important for stockholders	Infrastructure Investments
AI is in early experiments	Interactive Entertainment is Trending
AI R&D investment	IP Licensing
AI supercharges	Long Training Time of AI
AI to detect rendered glitches	M&A Integration Challenges
AI to Enhance Realism	Mitigation of ethical risks
AI to Push Boundaries	More Iterations is a focus
AI to Uplift to Character Likeness	Need to meet Development Deadlines
AI's emissions impact	New Experiences is a focus
Bias Risks	Open Patents
Business Model - Single Game Purchase	Open to New
Business Model: F2P	Operational/External Shock
Business_Model: Subscriptions	
Competition as Innovation Driver	

Player Base	Strategy: Blockbuster Storytelling Strategy
Power of Game Devices	Strategy: Business Model Diversity
Production Complexity	Strategy: Community management
Quality of Customer Service is important	Strategy: Core Business
Quality of Testing is important	Strategy: Device Diversity
R&D Investment	Strategy: Expansion of Genres
Readiness: Organisational (Talent)	Strategy: Expansion to Mobile
Readiness: Technological Context	Strategy: Live Services
Regulatory Risks	Strategy: M&A
Reputational Risks	Strategy: Online Communities
Research - Asset Creation	Strategy: Product Differentiation
Research - Asset Quality Verification	Talent as a Key Factor
Research - Fraud Detection	Talent dedicated AI training
Research - Generative AI evaluation	Talent Incentives
Research - Path Finding	Talent Support
Research - Procedural Content Generation	Talent Training
Revenue Concentration	Trend - Big Franchises
Risks Missed Opportunities pushes innovation	Trend - Cloud distribution
Safe Environments for players is a focus	Uncertainty re New
Safe Work Environment is a focus	User Generated content is a focus
Security/Cyber Threats	Value of the player is bigger now
Socially-connected ecosystem is a focus	Work with Cloud Providers