CATÓLICA LISBON
BUSINESS & ECONOMICS

Portfolio Company Value Creation: When Private Equity Deploys AI

Moritz Maximilian Mueller

Dissertation written under the supervision of professor Peter V. Rajsingh PhD

Dissertation submitted in partial fulfilment of requirements for the MSc in International Management, at the Universidade Católica Portuguesa, 05.04.2023

Abstract

This study concerns the role of artificial intelligence (AI) in private equity (PE portfolio companies) for developing and implementing efficiencies. Triangulating findings from current scholarship, expert interviews, and a consumer survey, our investigation revealed that AI is perceived as a significant disruptor, with the potential to transform PE operations and create value for portfolio companies.

The research highlighted several advantages of AI initiatives for PE portfolio companies, including strategic guidance and providing critical resources and management alignment. Furthermore, the survey demonstrated that consumers are receptive to AI applications in PE. However, the paper also identified limitations which could potentially hinder successful adoption of AI in portfolio companies. The efficacy of PE AI initiatives was found to be contingent upon the specific circumstances of each portfolio company, with benefits likely to be minimal or not present for AI-native firms.

Thus, while certain challenges persist, our findings underscore the importance of PE funds focusing on developing core AI competencies to harness AI efficiencies across their portfolio companies.

Keywords: Private Equity, Artificial Intelligence, Machine Learning, Competitive Advantage, Value Creation
Title: Portfolio Company Value Creation: When Private Equity Deploys AI
Author: Moritz Mueller

Sumário

Este estudo diz respeito ao papel da inteligência artificial (IA) no capital privado (empresas de carteira de PE) para o desenvolvimento e implementação de eficiências. Triangulando os resultados das actuais bolsas de estudo, entrevistas com peritos, e um inquérito aos consumidores, a nossa investigação revelou que a IA é vista como um perturbador significativo, com potencial para transformar as operações de PE e criar valor para as empresas da carteira.

A investigação destacou várias vantagens das iniciativas de IA para as empresas de portefólio de EP, incluindo orientação estratégica e fornecimento de recursos críticos e alinhamento da gestão. Além disso, o inquérito demonstrou que os consumidores estão receptivos a aplicações de IA em PE. Contudo, o estudo também identificou limitações que podem potencialmente impedir a adopção bem-sucedida de IA nas empresas de portfólio. Constatou-se que a eficácia das iniciativas de IA depende das circunstâncias específicas de cada empresa do portfólio, com benefícios que provavelmente serão mínimos ou não presentes para as empresas nativas de IA.

Assim, embora persistam certos desafios, as nossas conclusões sublinham a importância de os fundos de PE se concentrarem no desenvolvimento de competências centrais em matéria de IA para aproveitar a eficiência da IA nas empresas do seu portefólio.

Palavras-chave: Private Equity, Inteligência Artificial, Aprendizagem Automática, Vantagem Competitiva, Criação de Valor
Título: Criação de Valor da Empresa Portfolio: Quando o Private Equity implanta a IA
Autor: Moritz Mueller

Acknowledgments

First and foremost, I want to take this opportunity to express my deepest gratitude to my dissertation supervisor Peter V. Rajsingh. Without his expertise and efforts this dissertation would not have turned out the same. I could not have thought of a better professor to help me work on this challenging topic as the final step in my academic journey at Universidade Católica Portuguesa. He helped me envision my ideas clearly when I could not and provided constant feedback and guidance. His commitment and availability proved vital during this entire process and made this a great learning opportunity.

Additionally, I want to thank all my experts who took time out of their busy schedules to provide valuable insights and helped me create this piece. Moreover, I want to thank everyone who completed my survey to gain gauge at this topic from a different perspective.

Finally, I want to thank my family for their ongoing support through my entire academic career and everyone I met along the way. My journey in Lisbon simply would not have been the same if it was not for all the new people, and friends, with whom I created everlasting memories with. I want to take this moment to mention my close friend Paul Hauschild who accompanied me through many ups and downs. Another special mention goes to Kristina Schmitz for all the countless laughs and struggles we faced while writing our theses.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI – Artificial Intelligence
AGI – Artificial General Intelligence
AM – Asset Management
AUM – Assets Under Management
CAPM – Capital Asset Pricing Model
DA – Direct Alpha
DI – Disruptive Innovation
DSS – Decision Support System
EI – Efficiency Innovation
GP – General Partner
IRR – Internal Rate of Return
LBO – Leveraged Buyout
LP – Limited Partner
LTV – Loan-to-Value
MBI – Management Buy-in
MBO – Management Buyout
ML – Machine Learning
MOIC – Multiples on Invested Capital
NPV – Net Present Value
PE – Private Equity
PE AI – Private Equity deploying Artificial Intelligence in Portfolio Companies
PME – Public Market Equivalent
PV – Present Value
SI – Sustaining Innovation
SPAC – Special Purpose Acquisition Vehicle
VC – Venture Capital

Introduction

PwC recently deemed this technology to be the "biggest commercial opportunity in today's fast-changing economy" (PwC, 2017, p.1). Corporate investment has been ramping up at a CAGR of 31.97% between 2016 and 2021 (Thormundsson, 2022). The field is expected to increase global GDP by up to 14% in 2030 (PwC, 2022). Furthermore, the fastest-growing consumer application with 100 million monthly active users after two months (Hu, 2023) and news such as approval for the first self-driving taxis in China (Huang, 2022), the discovery of the highly potent antibiotic *Halicin* (Stokes et al., 2020), and the first ever image of a black hole (Lin et al., 2020) – are only made possible with this technology.

The common denominator for all of the above is **Artificial Intelligence (AI)** or, more specifically, **Machine Learning (ML)**. Although an imprecise usage, ML models are commonly treated interchangeably with the generic term AI. They are increasingly applied across the financial sector, such as in asset management, algorithmic trading (OECD, 2021), SME financing (Gambacorta et al., 2019), venture capital (VC), and private equity (PE) (Astebro, 2021). In PE, use cases range from due diligence support, including cash flow predictions (Dadteev et al., 2020) and data exploration (Carroll, 2022), and deal sourcing (Astebro, 2021), to AI solutions applied to portfolio companies (Carroll, 2022).

Even though AI start-ups attracted more capital than any other tech area in 2021 (Geronimo, 2022), only a minority of PE/VC firms (E.g., EQT Ventures, Jolt Capital, or 645 Ventures) are currently using AI to assist with investments decisions. Yet, 90% of PE firms expect AI to disrupt the sector by 2024 (Intertrust, 2018). Gartner even predicts that more than 75% of executive reviews for VC and early-stage investors will use AI and data analytics (Rimol & Costello, 2021). Other major funds, such as Steve Cohen's Point72 Hyperscale, apply AI solutions to help their portfolio companies capture value (Point72 Hyperscale, 2023).

Although AI and ML are mature concepts, recent advances in computing power and big data have enabled more sophisticated AI/ML to be applied in concrete use cases (Brynjolfsson & McAfee, 2017). The literature tends to focus on AI as decision support systems (DSS) for PE firms (Astebro, 2021) or non-accredited private equity investors (Vroomen & Desa, 2016).

Clearly, PE firms are not only investing in AI and using it as DSS but also applying it to portfolio companies. Thus, it is useful to examine the effects this novel phenomenon produces for companies as single entities, the industry in general, and the competitive landscape and broader market. This study aims to help develop this area of research.

The Research Question being interrogated is:
Does applying AI to PE portfolio companies create value?

Academic and Managerial Relevance

PE is a multi-billion industry. McKinsey states that in 2021, “fundraising was up by nearly 20 percent year-over-year to reach a record of almost $1.2 trillion; dealmakers were busier than ever, deploying $3.5 trillion across asset classes; and assets under management (AUM) grew to an all-time high of $9.8 trillion as of July, up from $7.4 trillion the year before” (McKinsey, 2022). With AI being such a significant influence on global economic output (PwC, 2022) and PE being a "high-powered way to optimize operations, financing, governance, and ultimately returns" (Brown et al., 2020, p.19) it is meaningful examining the novel interface of both domains. This is especially significant given that PE-backed companies are more likely to deploy AI solutions than their non-backed peers (Carroll, 2022).

Literature Review

Artificial Intelligence

Introduction to AI and AI in Finance.

Introduction to AI

Artificial Intelligence, first coined by John McCarthy at Dartmouth College in 1956, is an overarching term describing a broad spectrum of methods for *"making intelligent machines, especially intelligent computer programs"* (McCarthy, 2007, p. 2). Definitions of AI vary from thinking or acting in a manner analogous to human intelligence (E.g., an AI passes the Turing test) to acting in accordance with logical rationality. There is also debate about whether machines can actually think, if consciousness is necessary for artificial intelligence, or whether machines are simply simulating thinking-like behavior. Advocates of human-level AI believe the ultimate goal for an intelligent machine is to actually think, learn, and create across various contexts. Thus, creating "strong AI" or the closely related concept of Artificial General Intelligence (AGI) is juxtaposed with the more popular notion of producing rational, intelligent agents capable of simulating human traits and using them to attain the best (expected) outcomes for given tasks (Russel & Norvig, 2016).

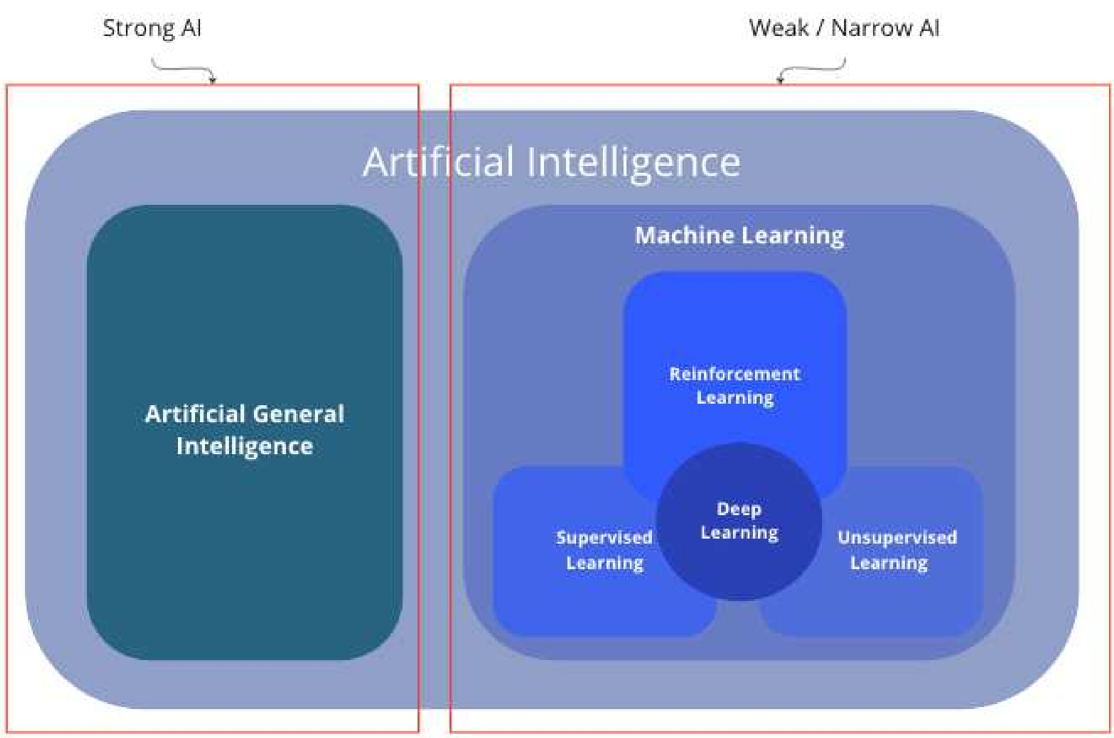

Figure 1: AI and its subfields (following Kavlakoglu, 2020; Murphy, 2022)

In contrast to strong AI, “weak” or “narrow AI” refers to an agent’s ability to be on par with or perhaps exceed human abilities regarding a specific task (IBM, n.d.). Traces of weak AI are evident in everyday life, e.g., chatbots, digital assistants, spam detection, or translation services (PwC, 2017; Russel & Norvig, 2016; Caswell & Bapna, 2022). Another commonly used distinction for AI methods is the symbolic and sub-symbolic classification. Symbolic refers to methods for knowledge representation, logical reasoning, or natural language processing. Sub-symbolic methods, on the other hand, include neural networks and machine learning (Schmid et al., 2021).

The previously mentioned examples of weak AI also implicate ML, whereby an algorithm’s ability to perform a specific task improves through repeated exposure to it while optimizing for given performance measures (Mitchell, 1997). Training happens through supervised, unsupervised, or reinforcement learning, depending on the model’s purpose. Supervised learning is the prevalent method used for classifying objects or predicting outcomes. Here, the model is exposed to a pre-labeled dataset – the training set – and improves by comparing its results with labeled input-output pairs until labels for any given input can be predicted accurately. An obvious downside is the long-time horizon and costs of collecting training sets (Murphy, 2022).

Unsupervised learning, alternatively, uses unlabeled inputs without receiving direct feedback. A trained model can be used to understand inputs and identify data clusters (Russel & Norvig, 2016; Murphy, 2022). With reinforced learning, an intelligent agent refines its model by receiving sporadic negative or positive feedback on outputs. Since it does not receive indications on which specific action led to the feedback, it has to weigh its actions according to the feedback received. As a compensation measure, supervised or unsupervised learning can be introduced to the model (Murphy, 2022).

Another form of ML algorithm is deep learning. This is based on the structure and function of the human brain, requires more computing power, and is the closest related concept to human-level AI (IBM, n.d.). It utilizes multiple layers of an interconnected network of “neurons”. Every "neuron" can process input data and produces an output. Deep learning refers to the number of layers utilized (Goodfellow et al., 2016). A network consisting of an input layer, at least one hidden layer, and an output layer is called deep learning (Kavlakoglu, 2020). Deep learning algorithms can be trained like conventional ML algorithms and calibrated through backpropagation to minimize the error between predicted and actual output. Backpropagation adjusts parameters in the direction that reduces the initial data until a model-data fit is provided (LeCun et al., 2015). However, this can lead to overfitting, meaning the model fits too closely to its training set. Thus, its results cannot be generalized as its performance on unseen data is insufficient (Goodfellow et al., 2016).

Since the 1980s, AI has been deployed in general management (Holloway, 1983) and towards competitive advantage (Porter & Millar, 1985), as well as being applied in business (Russel & Norvig, 2016). Nowadays, AI is frequently applied to achieve productivity, decision-making, customer and employee experiences, and innovation of new data-driven business models, all of which are oriented towards increasing company valuation (PwC, 2022).

Application of AI in finance

AI has multiple financial use cases ranging from PE to Decentralized Finance. Mentioning all of them would be beyond the scope of this paper. Thus, we will limit our examples to PE, Asset Management (AM), and Credit Lending. It is worth noting that some examples also apply to other financial sectors.

Current use cases in PE and AM include screening for potential investments, due diligence processes, and deal underwriting, thus creating operational efficiencies (Astebro, 2021; Blackrock, 2019; Haller & Campbell, 2022; OECD, 2021). Additionally, AI can help GPs and asset managers manage risks since ML models can run countless scenarios to assess potential outcomes (OECD, 2021). Another PE application is detecting opportunities for cross- and up-selling or add-on acquisitions through pattern recognition in big data, including alternative data formats such as GPS and satellite images (Blackrock, 2019; OECD, 2021). Thus, an AI has the potential to generate alpha for limited partners (LP) in novel ways. Asset managers also can benefit from pattern recognition and enhanced client experiences (OECD, 2021).

Another important segment is credit lending and insurance. AI can help reduce costs by creating efficiencies. Ant Financials MYBank brought down loan processing costs from RMB 2,000 to RMB 2 by applying their 3-1-0 approach: 3 minute application time –1 second for approval by AI and transfer of funds with 0 human interactions during the entire process (Iansiti & Lakhani, 2020). Such AI-driven approaches help open up access to credit for people with limited credit histories, etc. (International Finance Corporation, 2020; Langenbucher, 2020; Raso et al., 2018). Moreover, AI can lower costs and increase the fairness of processes by reducing noise – or unwanted variability – in repetitive decisions such as risk assessment in insurance policies (Kahneman et al., 2021).

AI-associated risks in finance

Both critics and advocates of AI are aware of the risks it brings in the financial sphere. However, at this point, further research is needed to analyze the impact of AI on finance.

Regulators, market makers, and actors are concerned about increased liquidity and systemic risks associated with herd behavior in capital markets. This phenomenon is exacerbated by actors with similar or interconnected ML models, while smaller players are more prone to herding if they rely on third-party AI providers (Bikhchandani & Sharma, 2000; Gensler & Bailey, 2020). Limited tech resources can mean market position concentrations when minor players are forced out (OECD, 2021). However, even larger entities without the necessary technological capabilities might need to exit (Astebro, 2021). Astebro (2021) also mentions higher barriers to entry as a negative. A major one being the substantial investments needed at multiples levels in the AI process (Mikalef & Gupta, 2021).

In addition, deep learning models could unintentionally collude if interconnected models spot interdependencies and adjust their *modus operandi* accordingly (OECD, 2021). This behavior might be hard to identify given the lack of transparency associated with AI decision-making (Calzolari, 2021), which is a major critique of systematic trading. Black boxes in asset management also pose issues where portfolio managers need to explain their decision processes to investors (OECD, 2021).

Besides the aforementioned financial risks, AI also implicates non-financial considerations such as data quality, data privacy and confidentiality, and cyber security (Calzolari, 2021; OECD, 2021; Stahl & Wright, 2018; Zou & Schiebinger, 2018). While AI may have an anti-discriminatory effect on lending, which promotes financial inclusion (Raso et al., 2018), it could also lead to undesirable practices if data used to train models are biased (Calzolari, 2021; Fuster et al., 2021). Famous examples of the effect of biased training data are Amazon's AI recruiting tool which discriminated against women (Dastin, 2018) and Meta and Microsoft chatbots, which exhibited racial biases (ODSC, 2022; Vincent, 2016). Raso et al. (2018) also highlight a potential chilling effect on speech and privacy if AIs used in credit aggregate examine everything one says or does when determining creditworthiness. Thus, ethical implications linked to AI are not trivial and need to be examined.

Private Equity

Overview

PE is an alternative asset class and began gaining traction following a clarification of the Employee Retirement Income Security Act in 1979 which opened it up further to large pools of retirement capital. It has also undergone several boom-and-bust cycles connected to various macroeconomic factors (Cornelius, 2011). Similar to AI, there is no consensus about whether PE should be treated as a broad asset class encompassing all parts of a firm's financing lifecycle or be defined more narrowly (Fraser-Sampson, 2010). Three major PE segments are buyout, venture capital, and growth capital. Buyout funds are the largest component of the sector, excluding real asset funds, and other fund types include infrastructure and public works (Bain, 2022). Since this paper will focus on buyouts, the terms PE, and Buyout Fund will be used synonymously.

	Leverage	PLC	Stake	Technology	Profits
Buyout	Yes	Mature/Decline	Maj	No	Yes
Development	No	Mature/Decline	Min	No	Yes
Growth	No	Growth	Min	Usually	Sometimes
Venture	No	Introduction	Min	Yes	No

Table 1: Main types of Private Equity at the company level (Fraser-Sampson, 2010)

Buyouts refer to a private equity firm acquiring a majority or controlling stake in a company that is already mature. Deals typically include debt financing, up to 90% of LTV in leveraged buyouts (LBOs) (Kaplan & Strömberg, 2009). Other forms include management buyouts (MBOs) and management buy-ins (MBIs). PE funds are almost exclusively limited partnerships and have a typical tenor of 10 years (Baker et al., 2015). The general partners (GPs) sponsor the operations while charging a management fee and taking carried interest (typically 2% and 20%, respectively) and LPs invest in the vehicle. Once LPs have committed capital, they are legally bound to provide funds when the GP makes a capital call. The number of LPs is, in theory, unlimited. They neither have decision-making authority over a fund and its portfolio companies nor liability as long as the GP's actions comply with the limited partnership agreement (Cornelius, 2011; Fraser-Sampson, 2010).

LPs are usually institutional investors such as pension funds, sovereign wealth funds, insurance companies, endowment funds, or family offices. They typically limit investment to less than 20% of their portfolio in a particular fund (Buchner, 2016). A target transaction for PE can be a public company that is being taken private, a private company, or a portfolio company of another PE fund. The latter is generally referred to as a secondary buyout (buy-side) or a sponsor-to-sponsor exit (sell-side). Exit options include sponsor-to-strategic, a sale to a corporate buyer, special purpose acquisition vehicles (SPACs), or initial public offerings (IPO) (Kaplan & Strömberg, 2009). Even though IPOs are typically the most profitable form of exit (Guo et al., 2011), sponsor-to-strategic is the most common form of exit, followed by sponsor-to-sponsor (see Figure 2) (Bain, 2022).

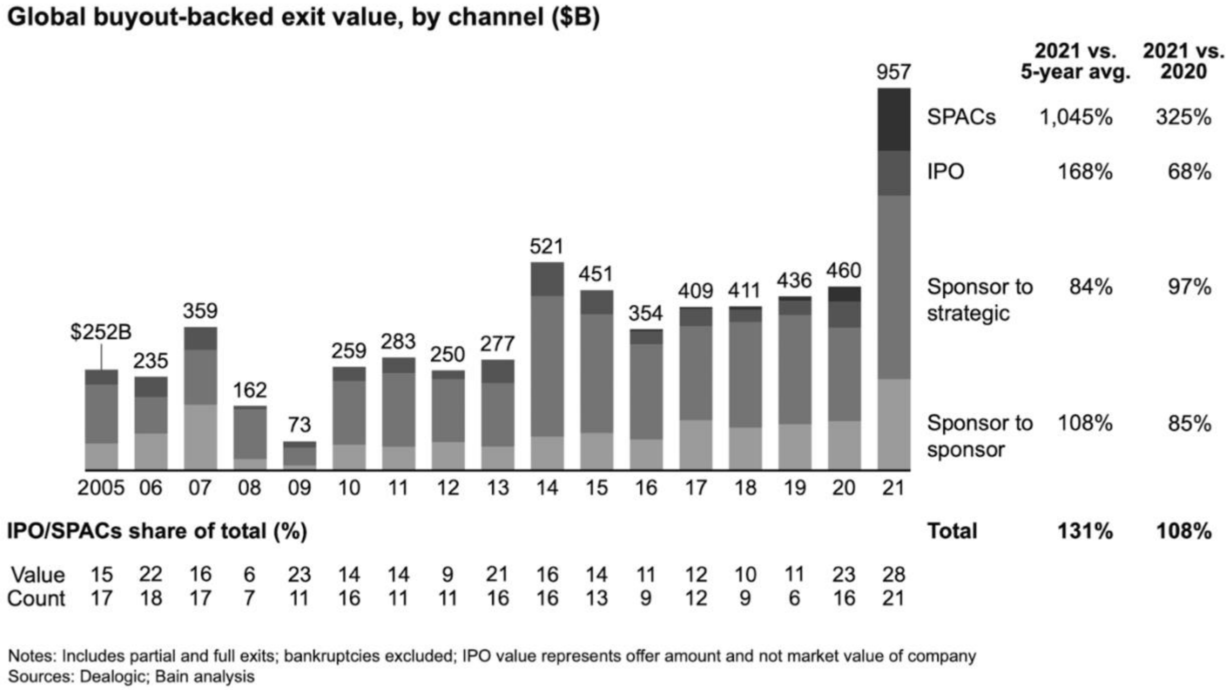

Figure 2: Global buyout-backed exit value, by channel (Bain, 2022)

Lastly, a significant difference between private and public equity is the illiquidity of PE investments. LPs cannot publicly trade their shares and are thus limited to secondary PE markets if they wish to exit their commitments prematurely. Capital calls are also unforeseeable for LPs, and committed capital must be held in liquid assets. Thus, market liquidity risk and funding liquidity risk can be associated with a premium the LP needs to recapture in terms of return (Baker et al., 2015).

Value Creation

In an earlier era of PE, GPs almost exclusively created value through financial and governance engineering. Thus, most value was produced on the day a deal closed. This thinking changed during the early 1990s recession when PE objectives moved more towards growth (Brown et al., 2020). Value creation for funds with vintages after this first era tends to happen through a third axis: operational engineering (Kaplan & Strömberg, 2009). Finally, the effects of PE on employees and society as a whole are secondary dimensions of PE value creation or destruction (Brown et al., 2020). Table 2 provides a brief overview of PE value creation and its evaluation.

Dimension	Summary
Measurement Methods	• Internal Rate of Return • Multiples on Invested Capital • Public Market Equivalent (Academia) • Direct Alpha (Academia)
Financial Engineering	• Changing capital structure, often through debt →Leveraging returns and tax-deductible interest payments • Diminishing as value driver in recent times
Governance Engineering	• Reducing agency problems and minimizing information asymmetries • Incentivizing management through equity participation • Oversight and guidance from GPs as concentrated owners
Operational Engineering	• Streamlining operations, cost-cutting, and efficiency improvements • Introducing new products, and fostering geographical expansion • Efficient working capital management and productivity improvements • Changes in strategy, better management practices, and alleviating financial constraints
Employee Dimension	• Attractive payout packages for senior management • Increased pay for high performers • Increased unemployment risk and lower wages for non-performers • Workplace injuries and safety violations decline
Societal Dimension	• Negative externalities in certain industries → higher ongoing medical costs and lower staffing levels in PE-owned nursing homes • Effective capture of subsidies in industries with government support may not lead to better consumer outcomes

Table 2: Summary - PE Value Creation

Measuring PE Performance

To assess value creation for GPs and LPs, one must look at returns generated by PE funds in excess of the benchmark (e.g., S&P 500) – also known as alpha (Fraser-Sampson, 2010). For LPs, these need to be net of fees to show actual cash returns. One of the most common approaches for calculating returns in finance is the Capital Asset Pricing Model (CAPM).

$$r_{CAPM} = r_f + \beta * [E(r_M) - rf],$$

where

r_f = risk-free rate

β = systematic risk of the cash flow

$E(r_M)$ = expected return of the market

CAPM is used to derive a discount rate from calculating an investment's present value (PV). A positive PV is achieved when the return on investment is higher than its cost of capital (Sorensen & Jagannathan, 2015). However, certain assumptions need to hold true for CAPM to be applicable. Returns are assumed to follow a normal distribution, and investors do not differentiate between upside and downside volatility (Buchner, 2016), meaning they are agnostic about higher or lower standard deviations from the target return. Both of these conditions are not satisfied in PE. Thus, using CAPM in PE does not capture the sector's systematic risk and abnormal returns (Buchner, 2016). While there is a dynamic extension of CAPM proposed by Rubinstein (1973) that can be used for approximating past PE performance, among other things it assumes frictionless markets and log utility preferences of LPs, it still requires estimating PE betas, which change due to financial and operating leverage (Sorensen & Jagannathan, 2015). Estimating PE betas is also problematic and potentially meaningless due to the illiquidity of such investments (Brown & Kaplan, 2019).

The prevailing method is to assess PE performance in terms of multiples on invested capital (MOIC) and the internal rate of return (IRR) (Gompers et al., 2016). After accounting for management fees and carried interest, the latter is used to appraise an LP's annualized return based on cash inflows and outflows to and from the fund. If the fund is not fully liquidated, the final cash flow will consist of the residual net asset value – an estimate of unrealized investment (Harris et al., 2014). Thus, discounting all IRR cash flows would lead to a net present value (NPV) of zero (Phalippou, 2008). Despite its frequent use, there are problems attributed to this method. It does not include a risk premium nor account for market returns, while it assumes that investors can reinvest future cash flows at the IRR (Sorensen & Jagannathan, 2015). GPs may also gerrymander IRRs by rigging the timing of cash flows (Phalippou, 2008; Sorensen & Jagannathan, 2015). Additionally, IRRs tend to overestimate a fund's performance due to averaging (Phalippou, 2008) and ignore the illiquidity factor of private capital markets (Ljungqvist & Richardson, 2003). Generally speaking, PE investors aim for IRRs between 20% and 25% (Gompers et al., 2016).

As a different measure, Kaplan and Schoar (2005) propose using a public market equivalent (PME). To receive the PME, the sum of all cash outflows of the fund (net of fees) (CO (t)) are discounted using the realized total return of any given public benchmark index from the start of the fund t=0 to the time of the outflow (e.g., S&P 500, EuroStoxx50, FTSE 100) ($r_M(t)$) and subsequently divided by the sum of all cash inflows (including management fees) (CI(t)), again discounted at the rate equal to the realized total return of the benchmark from t=0 to the time of the inflow.

$$PME = \frac{\sum \frac{CO(t)}{1 + r_M(t)}}{\sum \frac{CI(t)}{1 + r_M(t)}}$$

This measure compares PE returns to the return of a public benchmark. It enables LPs to "evaluate risk-adjusted performance without explicitly calculating any betas or even knowing the risk of the underlying investments" (Sorensen & Jagannathan, 2015). A PME greater than 1 outperforms the benchmark index (Kaplan & Schoar, 2005), meaning the fund generated excess returns for LPs. Regarding suitable benchmarks, it might be reasonable to adjust for the usually smaller size (in terms of market cap) of companies involved in buyouts (Brown & Kaplan, 2019).

Lastly, Gredil et al. (2023) propose the Direct Alpha method (DA) that combines measures from Kaplan and Schoar's PME and IRR, which discounts cash flows by a benchmark return. Thus, DA can be seen as an annualization of the PME and shows a more intuitive result.

Although there is no consensus on assessing PE performance, studies have applied various models to show the superior performance of different PE vintages relative to public equity markets. None of these found the average annual outperformance compared to the S&P 500 to be lower than 3% (Brown & Kaplan, 2019; Harris et al., 2014; Harris et al., 2020; Higson & Stucke, 2012; Phalippou, 2013). Brown and Kaplan (2019) also noticed that PE with vintages from 1994 to 2014 outperformed the MSCI ACWI every year. Nonetheless, there is a significant discrepancy between the performance of top-quartile funds and the bottom quartile. While top funds showed an average IRR of 30.6%, a MOIC of 2.74, and a PME of 1.81, bottom funds had, on average, a negative IRR of 1.4%, a MOIC of 1.00, and a PME of 0.68. This indicates that lower-performing funds do not outperform the public equity markets (Harris et al., 2020). A recent report by Bain (2022) supports these findings of divergent performances in the US and Europe (see figure 3). They also note that roughly 50% of LPs surveyed had PE returns exceeding their expectations in 2022.

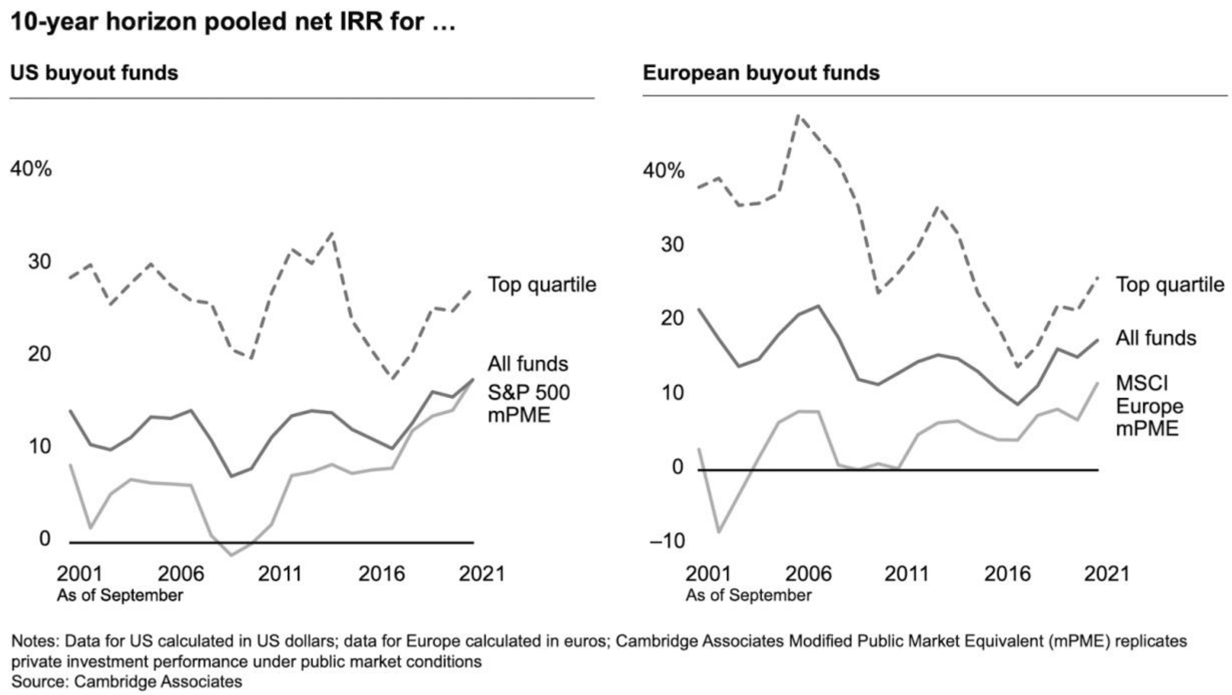

Figure 3: 10-year horizon pooled net IRR (Bain, 2022)

Financial Engineering

Financial engineering generally refers to changing a company's capital structure, usually by incurring debt to lever returns. Additionally, debt leads to interest payments being tax deductible (Kaplan & Strömberg, 2009). However, a higher debt burden also increases the risks of financial distress (Keasey et al., 2015). A 2013 study even suggests that easy access to credit causes overpriced deals and lower returns (Axelson et al., 2013). Nowadays, financial engineering is diminishing as a value driver (Braun et al., 2017), and less leverage tends to be used (Brown et al., 2020).

Governance Engineering

PE firms try to reduce agency problems by minimizing information asymmetries (Brown et al., 2020) and adequately incentivizing management (Kaplan & Strömberg, 2009) as part of governance engineering. Due to the illiquidity of private assets, management cannot sell shares before an exit, and this mitigates focusing simply on short-term performance (Kaplan & Strömberg, 2009). Leverage also requires management to make conscious budgeting decisions not to waste free cash flows on value-destroying activities since interest, and principal payments need to be made (Jensen, 1986).

A third form of governance engineering is the oversight and guidance GPs provide as concentrated owners (Guo et al., 2011). They tend to be more active than board members of non-PE companies and readily replace management for nonperformance (Kaplan & Strömberg, 2009).

Operational Engineering

Multiple studies from several industries suggest positive effects of GP management on portfolio companies with respect to operational performance (Acharya et al., 2012; Brown et al., 2020; Garcia-Gomez et al., 2020; Gompers et al., 2016) and operating profitability (Cohn et al., 2022). This occurs through streamlining operations, layoffs, which are more common in public-to-private transactions (Obernberger, 2022), providing access to expertise (Bain, 2022), and other levers. Cost-cutting is hence a major source of value creation (Kaplan & Strömberg, 2009).

Another strategy is increasing sales (Acharya et al., 2012). In the consumer industry, portfolio companies, on average, increased sales by 50%, compared to control firms, by introducing new products and fostering geographic expansion (Farcassi et al., 2017, 2020). Contrary to a common view from critics of PE that buyouts lead to substantial price increases for consumers, Farcassi et al. (2017, 2020) only found evidence of a marginal price increase of around 1%. Consequently, consumers can benefit from more product variety without higher prices.

Other forms of operational engineering include more efficient working capital management (Guo et al., 2011), overall productivity improvements (Davis et al., 2021; Garcia-Gomez et al., 2020), changes in strategy or strategic repositioning (Kaplan & Strömberg, 2009), and better management practices such as effective targets, performance monitoring and incentives (Bloom et al., 2015). Additionally, PE firms can alleviate the financial constraints of portfolio companies, helping them to seize growth opportunities, including add-on acquisitions that were previously out of reach (Boucly et al., 2011; Farcassi et al., 2017, 2020). This seems to be especially true in private-to-private buyouts (Cohn et al., 2022).

Bernstein and Sheen (2013) show that PE creates operational value through management from another perspective. They researched restaurants and noticed that in situations where PE has limited operational control at a store level (such as in franchise systems), there were qualitative differences in cleanness, safeness, and overall maintenance. Additionally, GPs with industry expertise and oversight improve operational performance more than GPs without expertise. According to Bain (2022), this expertise is particularly important in tech.

Employee Dimension

Looking at post-buyout companies, one must differentiate between senior management and other employees. Since management incentives constitute a significant factor in PE, senior management can usually expect attractive payout packages. GPs minimize agency problems between company owners and senior management by allowing them to participate in valuation upsides. Additionally, private companies' senior management is less subject to regulators and the public (Brown et al., 2020). For non-senior management, there is increased post-buyout unemployment risk and lower wages (Cohn et al., 2021). Empirical evidence supports this claim (Garcia-Gomez et al., 2020).

Regarding workplace injuries, Cohn et al. (2016) found a 17% decline for U.S. LBOs between 1997 and 2007, whereas the same authors found an 11% to 15% decrease from the mean in a later study (2021). Both studies notice that lower rates of workplace injuries occur in the second year post-LBO and last at least until the fifth year. Considering the negative correlation between workplace injuries and public valuations, this might also be a factor for value creation for GPs and LPs (Cohn & Wardlaw, 2016). Additionally, public buyouts of US firms lead to reduced Occupational Safety and Health Administration (OSHA) violations, which reduces associated fines (Cohn et al., 2021).

Societal Dimension

As shown, PE buyouts create value on multiple levels. Nevertheless, when it comes to effects on broader society, empirical evidence suggests several negative externalities. One example is in PE-owned nursing homes. On average, compared to their non-PE-backed peers, these institutions had fewer and less-skilled registered nurses (Pradhan et al., 2014). Thus, social burdens are imposed due to higher ongoing medical costs. A later study confirmed the results, linking fewer front-line nursing staff and higher bed utilization to adverse health outcomes and noncompliance with accepted norms (Gupta et al., 2020).

A Dutch study of 56,000 employees also suggests a negative impact on society when workers with poor health face loss of income or employment after PE buyouts and consequently need state support (Garcia-Gomez et al., 2020). Moreover, PE funds are good at capturing subsidies and maximizing value in industries with government subsidies, such as higher education. But this does not necessarily generate better outcomes for consumers since PE here was associated with higher tuition and per-student debt, lower graduation rates, and lower earnings (Eaton et al., 2020).

The evidence above generally implies that profit-maximizing, even with regulations in place, may not always align with social good or value creation for society (Brown et al., 2020).

Recent Trend: Democratization of PE

As fundraising takes longer and gets harder due to economic uncertainty (Farman, 2023; Mendoza, 2023b), GPs are looking to tap alternative, non-institutional sources for capital. Alternative sources mainly include ultra-high-net-worth individuals, but companies such as iCapital and Moonfare allow general retail investors to participate in PE investments starting from 10,000€ (De Beer, 2023). Additionally, the senate introduced the Retirement Savings Modernization Act in 2022, allowing ordinary Americans to more efficiently allocate their 401(k) contributions towards PE (U.S. Senate, 2022). Although individual investors hold 50% of global wealth, they only account for 16% of AUM in private capital (Skolnik et al., 2023). That is why some mega-funds, such as Blackstone, are openly welcoming this (unstoppable) trend of democratization and are starting branding initiatives to attract them (Mendoza, 2022; Mendoza, 2023a). However, including retail investors also creates new challenges, such as educating them on the vehicles they are investing in (Collins, 2022) or potential changes in the typical 2 & 20 fee structures, as retail investors might want to increase their share of returns by reducing the management fee and offering lower carried interests according to some experts (Le, 2023).

Management Theory and AI PE

With trends towards using more data and technology for diligence purposes (Haller & Campbell, 2022) and PE firms adopting AI for their own processes (Astebro, 2021), GPs are gaining first-hand experience in managing AI technologies. AI is a significant management lever experienced management can deploy to attain competitive advantage. Additionally, GPs are exposed to AI across corporations, industries, etc., and so technology can be levered for superior firm performance (Le Nadant et al., 2018) and value creation.

Mintzberg & Waters (1985) differentiate between deliberate strategies and emergent strategies. A strategy can be classified as deliberate when concretely specified objectives are communicated and shared by every affected actor. Strategic moves are executed as intended without external disturbances (e.g., regulatory change, market shifts) for a deliberate strategy to be realized. Thus, this static approach to strategy does not account for exogeneities influencing strategy as it is framed and executed as part of a complex system. Porter's (1996) conception of competitive strategy entails "deliberately choosing a different set of activities to deliver a unique mix of value" as well as managing the firm in light of his five forces (Porter, 1996). On the other hand, Mintzberg and Waters (1985) propose a more dynamic approach to firm strategy. Strategy becomes an emergent phenomenon as it interacts with external factors and becomes somewhat transformed from what was initially intended.

The notion of emergent strategy is important in light of complexity, where deterministic, linear, cause-and-effect thinking is inadequate for solving problems (Hossain et al., 2020). Complex systems are part of general system theory which defines a system as a network of interconnected actors constantly being changed as a result of engagement with the environment and other actors (Bertalanffy, 1968). Complex systems are characterized by ambiguity, emergence, adaptation, interconnectivity, feedback loops, non-linearity, and reflexive socio-economic factors (Hossain et al., 2020). One such complex system are financial markets (Kuhlmann, 2014). PE firms operate in a variety of complex systems ranging from financial markets to the industries associated with their portfolio companies. Additionally, digitalization has led to an even more fast-paced and constantly changing business landscape (Venkatraman, 2017). Thus, a dynamic approach to strategy is necessary for GPs and senior management of portfolio companies.

Studies conducted by Luftman (n.d.) between 2012 and 2017 show that alignment between IT strategy and business strategy significantly impacts performance (Luftman et al., 2017). In fact, this alignment was the preponderant concern of global CIOs in five of these six years (Luftman, n.d.) and continues to be so (Ben-Zvi & Luftman, 2021). Other researchers agree, including Borges et al. (2021) and Yeow et al. (2018). One of the reasons for alignment problems was the subordinated role of IT strategy, which is why a fusion of both, dubbed "Digital Business Strategy", was proposed by Bharadwaj et al. (2013). Shao (2019) suggests that leadership must spread motivation and inspiration to align both strategies.
AI is even more complicated as there is still too little knowledge concerning how AI can be implemented and applied strategically as a value-creation tool (Borges et al., 2021). Cultural obstacles, people (Bean, 2019), and process and workflow integration (Deloitte, 2021) seem to be the principal issues when implementing AI.

People can have negative and positive attitudes towards AI depending on the specific situation (Lichtenthaler, 2019), and to solve this, Pappas et al. (2018) propose a data-driven culture. This is supported by Deloitte's survey on the state of AI which puts data at the center of competitive business strategy (Deloitte, 2021). Others propose a so-called "cognitive strategy, "combining data, technology, people, and change management to generate positive returns from AI investments (Davenport & Mahidhar, 2018). Further, top management must align AI with business strategy (Deloitte, 2021). GPs and their hand-picked top managers need management expertise to create an AI ecosystem and explain AI results. This is supported by the fact that 83% of the current AI frontrunners carry out AI strategies through an ecosystem approach (Deloitte, 2021).

In addition to lodging the notion of AI in PE in the framework of emergent strategy, it can also be thought of in terms of Christensen's disruptive innovation. Christensen (1997) distinguishes three kinds of innovations: efficiency, sustaining and disruptive. Efficiency innovations (EI) generally relate to cost savings and reducing headcount, whereas sustaining innovations (SI) respond to changes in markets by seeking to increase the performance of a known product or service (Christensen & Overdorf, 2000).

Alternatively, disruptive innovations (DI) initiate radical changes and address entirely new markets through novel products or services (Christensen & Overdorf, 2000). Initially, DI tends to underperform existing solutions and are also niche phenomena slow to gain traction (Christensen, 1997). For this very reason, incumbents tend to favor EI and SI in known markets (Marvel & Lumpkin, 2007; Christensen, 1997). It is interesting to consider how we are to view PE AI in terms of Christensen's innovation typology.

Deploying PE AI can also be thought of as an emerging core competency (Prahalad & Hamel, 2009). Unlike Michael Porter's "outside-in" view, core competency theory takes the perspective of the "inside-out" and, in this regard, is in the same genre of management theory as the resource-based view (Barney, 1991) and dynamic capabilities (Teece et al., 1990 & 1997; Barreto, 2010).

Contribution to Literature

This thesis contributes to the extant literature by discussing a novel area associated with strategic management in a niche business domain with a significant market cap (PE). It also deals with a novel technological area (AI) associated with an emerging secular trend. The thesis also fills a gap insofar as few studies cover how deploying AI in PE adds value and creates a competitive advantage.

Methodology

Given the effectiveness of GPs for creating value, the working hypothesis being tested is that PE-backed companies applying AI can better create and capture value than their non-PE-backed peers.

A review of the literature, semi-structured interviews and a survey provide the methodological grounding of this thesis. This triangulation approach was chosen to cross reference both AI and AI implementation challenges, identified in the interviews, with advantages PE offers portfolio companies explored in the literature review and expanded in PE expert interviews. Lastly, in line with recent trends of financial inclusion in PE, consumer sentiment towards AI and its effects on perceived value were analyzed.

Qualitative Data

Due to complexities associated with our research topic and the need to gather expert opinions on this novel phenomenon (Barriball & While, 1994), semi-structured interviews were chosen to collect qualitative data. The flexible interview guide was based on insights gathered through the literature review (Turner, 2010).

In total, 17 experts experienced in either AI, PE, or both were interviewed. AI experts were drawn from business or research backgrounds. Questions were adapted according to each group, and follow-up questions were phrased to facilitate participants' understanding and gain additional insights (Turner, 2010). One expert was a generative AI based on natural language processing to showcase AI's potential.

Code	Occupation	Company
Expert A	AI PhD Resident	Major US AI Research Lab
Expert B	Principal	US PE Fund
Expert C	Director; Head of AI & Data Science DACH	Major Tech Company
Expert D	Principal	Hongkong PE Fund
Expert E	Team Lead	Norwegian Quantum Computing Research Lab
Expert F	Associate	US PE Fund
Expert G	Founder	US ML Startup
Expert H	Founder; Managing Partner	German PE AI Fund
Expert I	CEO	AI Implementation Consultancy
Expert J	Director Portfolio Operations	UK PE AI Fund
Expert K	Managing Director EMEA; Professor	Tech Company
Expert L	Data Scientist	German Scale-Up
Expert M	Managing Partner	Portuguese PE Fund
Expert N	EMEA Trustworthy AI Lead; Vice-President AI Research	Major Tech Company
Expert O	BI Consultant	German BI Consultancy
Expert P	Senior Associate	UK PE Fund
Expert Q	Generative AI	Major AI Lab

Table 3: List of Experts

Overarching topics across all groups were a general understanding of AI in business, potential systemic risks, and the notion of PE funds deploying AI capabilities in companies. Some questions were common to all groups to enable a cross-group analysis on certain AI topics.

The interview questions for PE and AI Experts can be found in Appendix A and B, respectively.

Due to the limited number of PEs using AI, there was more general discussion about AI in PE and how the funds can leverage AI capabilities to give their portfolio companies an advantage.

Quantitative Data

In light of the democratization of private markets, we conducted a consumer survey. This sought to understand whether the current model of PE can continue if the source of value creation shifts to AI. The survey analyzed public sentiment in the US, UK, and Germany, all markets with a significant share of high-net-worth individuals (Statista, 2023). We addressed a nationally representative sample of N=300 for each country. Thus, selection bias was minimized. The data from all three countries were then merged to perform cross-country analyses. A full version of the questionnaire can be found in Appendix C.

We were interested in the various levels of knowledge about AI and ML to see if differences exist between countries and how perceived knowledge affects perceptions towards AI. To assess the initial survey question, different scenarios were created. First, a general scenario was presented to see if AI created expectations of cost reductions. This assumption is based on evidence from several industries where automation of processes leads to reductions in labor, operations, logistics, and overhead costs (Ivanov & Webster, 2017; Ohno & Bodek, 1988; Rueßmann et al., 2015). A second scenario about personal investing was then given to mirror the fee structures of PE funds for institutional investors. We chose to use this scenario instead of an actual PE example because we did not want lack of knowledge about PE to interfere with results. Lastly, we ended with questions on AI decision-making and potential ethical implications.

We used structured questions with a 5-point Likert scale because research suggests that the reliability of answers does not increase beyond a 5-point scale (Lissitz & Green, 1975). However, respondents may have reverted to the middle since a 5-point scale does not force a choice. Thus, results might have a central tendency bias.

Results

Qualitative Analysis

Following the interviews, inductive analysis was performed to derive and categorize findings (Mayring, 2014). No demographics besides experts' experience within their respective subjects were recorded for privacy reasons. Using transcriptions, the interviews were coded in line with the aforementioned methodology. The top-level categories for PE and AI include Value Creation for both topics and PE AI, as well as AI Challenges and Attitudes towards AI. The latter also includes codes that do not relate to any of the other buckets. Second-tier categories include codes that were mentioned five or more times. For clarity purposes, we aggregated codes with less than five mentions and displayed them as Other. Due to the secondary nature of insights for answering the RQ, the second-tier categories of AI & PE Value Creation and Attitudes were analyzed in an aggregated form. Second-tier categories within the Challenges and PE AI were analyzed individually as they directly relate to the research question. Nonetheless, an overview of both topics is presented by considering the results of the top categories with Value Creation first.

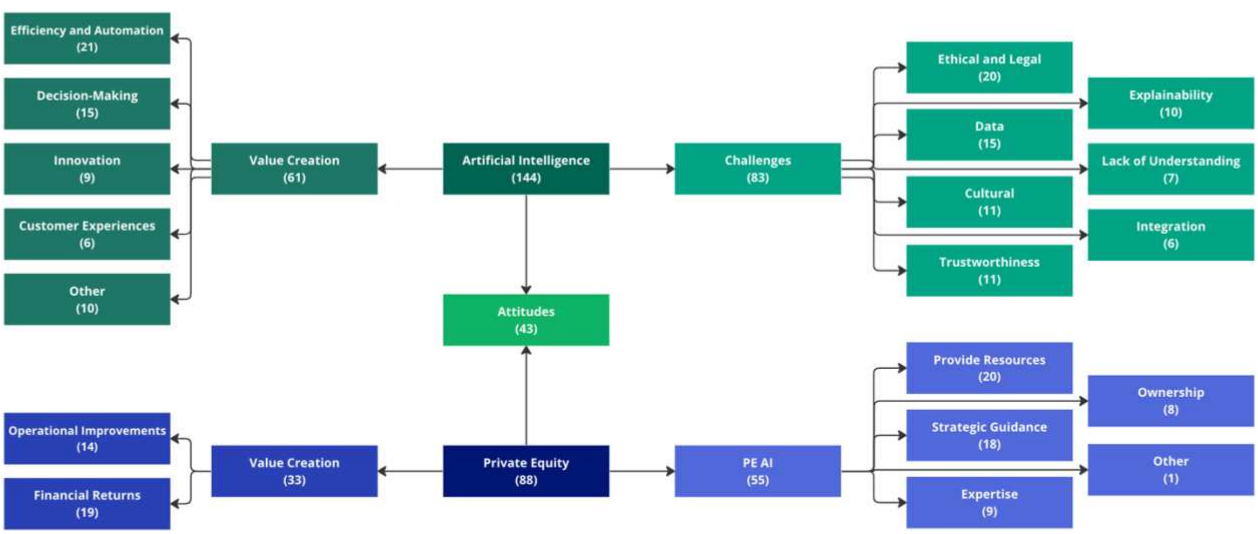

Figure 4: Inductive interview categories

AI Value Creation

AI can be seen as a tool for overall operational improvements (Expert G). Expert I even stated that he has yet to encounter any function or sector where it cannot create value. Nonetheless, some appliances can even be regarded as major opportunities. One of these major value drivers for businesses is using AI to generate efficiencies and cost reductions through automation (Expert

N) and resource management (Expert O). Experts K and J mentioned maintenance checks as a quick win for companies. Implementing a control algorithm makes it unnecessary to always send maintenance personnel for routine check-ups. Thus, AI enables opening up schedules for more demanding tasks that require creativity and critical thinking – both attributes currently not provided by AI.

Additionally, chatbots can be implemented to deal with frequent internal and external requests (Expert C). Customer satisfaction will rise as chatbots get more sophisticated over time. Customers can also receive more personalized marketing content to directly address their needs (Expert I; Expert L). Expert I even mentioned that they no longer produce the content themselves.

A second major driver stated by many experts was enhanced data-driven decision-making by analyzing large amounts of data (e.g., Expert E; Expert Q). This can be especially helpful within complex non-linear business cases (Expert O). Applying algorithms can remove emotion from decisions, making the process leaner, fairer, and less biased (Expert F). However, Expert C emphasized that certain decisions, such as layoffs, need emotions and other considerations that AI cannot achieve.

Lastly, AI has "huge potential and innovation power, which is why it is so disrupting" (Expert N). According to several experts, it can not only help to develop new products such as medicine but also transform entire industries, business models, and the workforce (Expert E; Expert G; Expert O).

All experts agreed that the future of AI looks bright and that it can do "everything it can do now, just better" (Expert O). Expert E and Expert K suggested that the commercialization of quantum computing will be a massive multiplier for AI. This will make AI a commodity "just like electricity" (Expert K) and a tool to counter ageing societies in the future. Human-AI collaboration will most likely play a vital role in society (Expert L), which might favor generalists over specialists (Expert A).

Challenges

This top-level category includes general issues associated with AI and challenges that can occur when companies develop and implement AI in their businesses. As this is directly related to answering whether PE can create value by deploying AI, this category had the highest count with 83 overall mentions.

Ethical and Legal

This sub-category was the most mentioned category in this bucket and was counted 20 times. However, challenges such as biases were often only briefly mentioned and not further elaborated on because they are commonly known.

According to Expert Q, companies must consider subjects such as data privacy and security, bias and fairness, and transparency when considering AI's ethical and legal implications. One of the experts placed specific focus on security concerns as she did “not understand how no one talking about AI is mentioning cyberattacks in the same breath” (Expert K) since more data and digital assets provide a larger surface for those attacks. Expert A extended this concern from data of individuals to commercial data as well. Hiring third-party AI developers or consultants creates greater potential for sensitive data leaks, which is even more significant for companies basing their value proposition on algorithms and data. Additionally, data privacy and security are important levers to make AI trustworthy (Expert C), which the EU AI Act emphasizes (Expert C; Expert N).

Expert N remarked that using third-party developers might interfere with transparency as it is only clear sometimes what data the model is trained on, which metrics are used to measure performance, and who is accountable for the model’s outputs.

As a final remark, Expert E pointed out that ethical challenges are tough to solve as AI is binary, whereas ethics is not, meaning that no universal ethical code exists. He warned that AI recommendations, although potentially profitable in the short term, might turn out to be value destructive in the long run. Expert N added that awareness of ethical, social, or regulatory implications needs to be raised as many organizations are not used to thinking about them.

Data

Two critical issues cited by almost every AI expert when it comes to developing AI capabilities for businesses are data availability and the quality of data. “Algorithms rely on large amounts of high-quality data to learn and make accurate predictions” (Expert Q). The quality of input data is directly correlated with the quality of outputs (Expert J), and only high-quality data leads to valuable AI initiatives (Expert D). Expert E added that this is why humans always need oversight over which data AI should learn from since algorithms cannot differentiate between high- and low-quality data or relevant and irrelevant information. Currently, many companies do not keep good data, which is the biggest obstacle, according to another expert.

Additionally, not only missing data but inaccurate or manipulated data adds to the problem (Expert A). Many profitable AI features cannot be implemented due to the need for more data. Thus, the unavailability of high-quality data limits the potential of AI (Expert D). Expert N emphasized the importance of availability because AI cannot predict outcomes when there are entirely new scenarios without existing data. The worst case is an algorithm recommending something false because of it. Experts E and L seconded this. Moreover, data helps track a company's environment (Expert A) and helps users understand why an algorithm is predicting or recommending something. This is also the reason why many PEs, compared to algorithmic traders, are not wholly reliant on models for due diligence, as it would need a lot of data to predict anything (Expert J), and private markets usually provide less data than public markets (Expert B; Expert D).

As a potential solution, Expert K recommended that companies start looking into using small high-quality data to do good things. She added that this is also important in light of resource efficiency, as big data needs a lot more energy. Usually, models trained on small amounts of data can achieve 80-90% accuracy and thus provide value for companies. Big data is only necessary for the remaining percent, so Expert I did not necessarily see availability as a key issue. Expert G agreed and compared data to oil – a commodity usually not mined and processed by the end user. He held that many people could use existing data sets and tweak their models for more narrow use cases.

Trustworthiness and Explainability

Two challenges often mentioned together are trustworthiness and explainability (Expert A; Expert C; Expert E; Expert G; Expert N). Experts A and C elaborated that trustworthiness is such an essential part of every discussion about AI because of the “Black Box Problem”. “People from the outside cannot look into the engine of AI” (Expert C). Therefore, they need to trust recommendations - another key focus of regulators (Expert C; Expert N).

Expert C added that explainability is one of five factors to facilitate trust, with the other four being transparency, robustness, IT security, and fairness. It can be a powerful accelerator for trust in areas of high risk (Expert N) or where people are negatively affected (Expert L). An example could be an automated decline of a loan application. Additionally, explainable AI (known as XAI) might facilitate adoption with experienced practitioners when non-parametric black box methods are accompanied by parametric explanations instead of them just having to listen to “machines” without explanation (Expert A). This notion is also crucial for accountability purposes. Employees would still need to take accountability for certain decisions and should thus understand where they are coming from (Expert N).

Lastly, it is also important for developers to understand and analyze fairness and introduced biases of the model (Expert O).

Cultural and Understanding

When implementing AI in businesses, Expert I considered fear of cultural change, and fear of job losses due to automation as the most significant challenges. As a third-party AI consultant and developer, he stated that educational work regarding AI is often more important than the technological development of capabilities. Besides the fear of layoffs, (Expert A) educational work is also required to set reasonable expectations. Expectations of AI are often too high and cannot be fulfilled, which might lead to negative attitudes towards the technology (Expert C; Expert L). However, Expert C highlighted that this is not unique to AI but occurs with every new technology.

Additionally, management support can be challenging as old-fashioned management teams might not be receptive to the change AI brings (Expert A; Expert F; Expert Q). Ongoing management support is especially important because innovation happens in increments, usually not disruptively. Thus, management needs to facilitate a culture where learning and development can occur to enable AI to thrive (Expert C).

Other

Other challenges mentioned included high costs for developing and implementing AI capabilities, especially for small and medium-sized companies (Expert Q). These costs are partly increased due to talent shortages in data science and AI, another challenge to master (Expert I; Expert Q).

PE Value Creation

The first thing every PE expert said when asked how they defined value creation in PE was financial returns oriented. Expert B explained the PE process as buying a stream of cash flows, leveraging them, and creating value by reducing leverage with operating cash. One expert put it simply as "the difference between value of equity at entry vs value at exit" (Expert H). Expert J framed value creation as “any activity that you can either incentivize or accelerate, or, you know, just apply into the assets that you are acquiring, such that the exit value is higher”. These can be initiatives that optimize the P&L or balance sheet through cost reductions or revenue growth. Expert P also mentioned bottom-line improvements, which can occur through product expansion or new market entries (Expert M). Moreover, Expert P explored a different dimension of value creation, including increased workplace safety and cyber security. This is aligned with some PEs recently taking into account ESG value creation (Expert F), although Expert B admitted that it is not too much of a concern.

Measuring PE value creation happens through IRR and multiples almost exclusively, or as Expert D put it: “There is only one measure of success in PE, which is IRR. So, whatever that drives, that is an aesthetic reason. That is how we get incentivized.” Expert B also pointed to peer comparisons as an option. Another expert also brought up business specific KPIs, such as churn rate for measuring portfolio company value creation (Expert F).

PE AI

This top-level category was mentioned 55 times and describes how PE can use its capabilities to minimize challenges that occur during the development and implementation of AI capabilities.

Provide Resources

PE can deploy AI with greater funding, as developing it is expensive (Expert C). An additional financial benefit can be lower costs for procurement processes as funds can leverage their power and network to get more beneficial terms (Expert P).

The network is also why Expert I would rate the advantage for PE-backed companies as four out of five compared to their non-backed peers. Expert D added that PE can help alleviate the talent shortage as they can either have their in-house data scientists and developers (also see Expert F; Expert J) or use their network to easily hire external developers, which Expert J seconds.

Expert D, Expert F, and Expert E agreed that PE can share data across portfolio companies to reinforce models efficiently and increase accuracy more than if each portfolio company were to build models individually. AI Expert N underscored that this can indeed be an advantage but depends on the specific industry.

Strategic Guidance

One of PEs' core competencies is identifying use cases for optimization (Expert C). By recognizing the potential for AI to optimize business, for instance, in the cost structure (Expert C), through automation or making processes lean, PE can kick-start AI initiatives in its portfolio companies (Expert K). Additionally, they can provide management with insights on why using AI is a better case than not using it (Expert D) and why it is necessary to avoid the common pitfall of treating AI as an "innovation center initiative […], that is on the sidelines, doing small projects that might end up being a proof of concept, living somewhere in a library and then never being used" (Expert J). Securing top-down alignment and convincing the C-suite that it should be part of the core business and is a technology that can improve all business areas is important (Expert J). Thus, PEs with the right experience can ensure that AI is used "with more purpose and for the right value" (Expert N) and accelerate the entire process (Expert K).

Later, PE can also provide guidance on which initiatives can be outsourced and which are essential to be developed internally (Expert K). Expert J's goal is to ignite a process, build a capability, and make the portfolio company self-sustaining in the future.

Expertise

Closely aligned with strategic guidance is the sub-topic Expertise. Due to PE expertise and knowledge transfer from other businesses across its portfolio (Expert I; Expert P), portfolio companies can potentially avoid a lot of pitfalls (Expert N) or, as Expert J put it: "Knowledge transfer is massive […] we are not allowing them to make the mistakes that we have seen other companies making". However, Expert P also stated that it is necessary to differentiate between companies without much data or AI experience compared to mature data companies, as PE might not be able to provide much value for AI strategies of the latter. Expert C agreed that PEs probably have lower AI capabilities than big tech and might not know all state-of-the-art AI tech.

Ownership

Another advantage that PE-backed companies might have in regard to implementing AI is top-down alignment due to ownership structure. "As owners, you can push through with topics that might otherwise not be on top of the management agenda" (Expert H). Expert N agreed that businesses and their management buying-in from the very beginning is leading to higher and faster adoption. Expert M added that PE ownership ensures that the management team is committed to using AI, even if they cannot precisely envision how it will work. Additionally, PE can use its ownership to make necessary personnel changes to drive the envisioned change (Expert K). Expert F highlighted that the alignment between PE and a company through the incentive system also ensures they provide the right kind of advice. This might be different for third-party consultants.

Attitudes

To assess overall attitudes, experts were asked about their opinions on AI being the biggest disruptor in today's business world and whether they would follow through on AI recommendations directly affecting human beings using a 5-point Likert scale. Additionally, they were asked if it is plausible for AI to make major decisions without human oversight and if they see increased systemic risks due to broad AI adoption.

Disruption, Morality, and Decision-Making

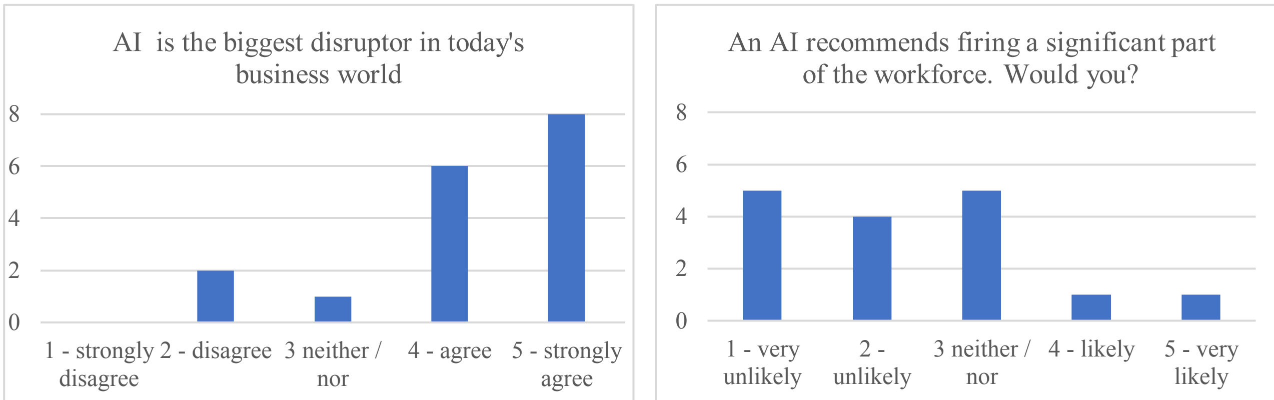

Figure 5: Likert Scale - AI Disruption and Morality

Figure 5 shows that almost half of the 17 experts strongly agreed with the statement "AI is the biggest disruptor in today's business world". Only two of them tended to disagree with Expert I, stating that AI has been around for too long to rate it as disruptive. When it comes to trusting AI on layoff decisions, nine out of 16 experts stated that they would not follow through with the recommendation because they would want to assess the situation themselves first. Nonetheless, 14 out of 17 experts believed it is plausible that AI can make major decisions without human oversight in the future, although they think it is not advisable (Expert H; Expert O). Experts D, E, and N emphasized that current AI cannot predict outcomes when there is an entirely new scenario, thus giving AI control over major decisions could be harmful. Expert J argued that there is no benefit in using AI for major decisions and recommended AI for a large volume of decisions when making quick optimal decisions is hard for human beings. This is partly why all but one expert advocated for humans always having a discretionary override. Other reasons were trustworthiness (Expert A; Expert J), ethical concerns (Expert Q), and future regulatory requirements such as the EU AI Act, which is "asking big time for human control, in particular for high-risk systems, all systems managing people, and when human bodies are at risk […]. There will be no AI firing people" (Expert C). Expert I disagreed and believes that deploying AI for decisions does not make sense if you do not trust it. As an example, he referenced the famous move 37 by Alpha Go which did not exist until the algorithm played it and won the match against the world champion in Go at that time.

Systemic Risks

Multiple experts anticipated increased systemic risk through herding behavior. The risk increases if the model is biased toward one particular group, lacks diverse training data, or lacks transparency (Expert Q). Algorithms based on similar data can also increase the risk of herding behavior. Another reason is AI's problem with only including relevant and excluding irrelevant data (Expert A; Expert E). Expert G predicted a short-term increase but a long-term decrease in risk due to AI leading to higher differentiation. Expert O argued that herding behavior is less likely because models take into account large numbers of factors and data points, thus making sophisticated decisions.

Consumer Sentiment

The survey data included 901 observations, with 50.5% of the participants being female. The average participant was 39 years old, the minimum age was 16, and the maximum was 65. As previously mentioned, our sample was nationally representative and contained 300 participants from the United States of America (US), 300 participants from the United Kingdom (UK), and 301 participants from Germany (GER).

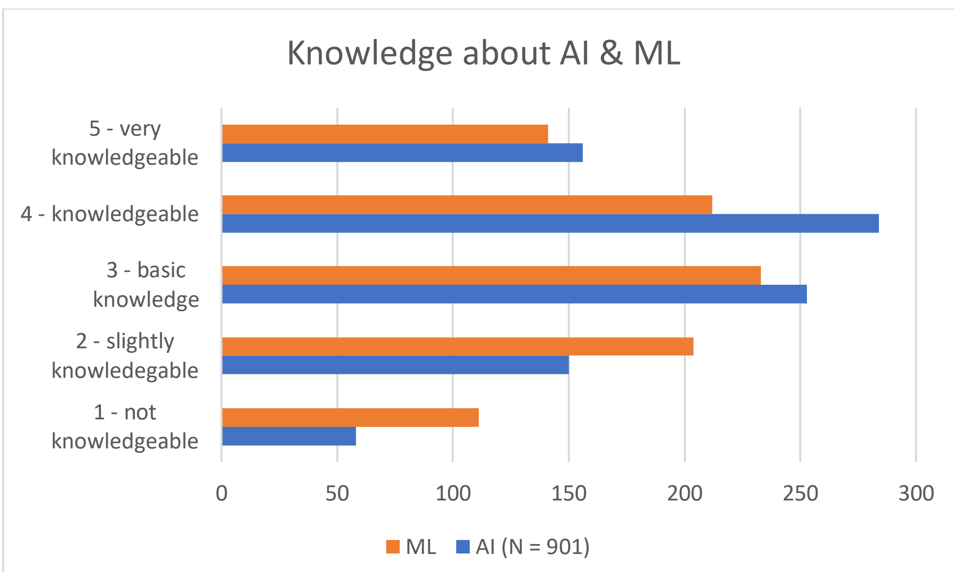

Figure 6: Consumer Survey - Knowledge about AI & ML

When asked about their AI knowledge, 63.3% of Americans considered themselves either knowledgeable (37.0%) or very knowledgeable (26.3%). These numbers dropped to 46.4% and 36.9% in the UK and Germany, respectively. While less than 5% of US and UK participants considered themselves not knowledgeable on the topic, 10.3% of Germans did so. These differences between countries are significant at a 1% level. 62.8% of all very knowledgeable participants were men, whereas 60.3% of not knowledgeable people were female – these differences were also significant at a 1% level. Narrowing down the scope to ML, on average, 18.4% fewer people considered themselves knowledgeable or very knowledgeable.

Participants were asked to rank a set of seven positive and negative emotions according to their feelings about the future of AI. This ranking was on an inverted scale; thus, a lower rank equaled a better position. Generally speaking, positive emotions (hopeful, excited, and confident) were, on average, ranked lower (3.82) than their negative counterparts (Anxious, Worried, Afraid, Confused) (4.14). People most often associate hopefulness and excitement as their primary emotional responses, ranking them first in 162 and 159 cases, respectively. The variable afraid was least likely to be ranked first (N=93) but most likely to be ranked last (N=245).
To understand the consumer perception of value creation through AI, participants were subsequently confronted with two scenarios. Scenario 1 consisted of a riskless surgery first performed by a doctor and then by an AI – where everything else, such as the medical briefing and risks, remained the same. Of the 680 participants willing to undergo surgery, 377 or 55.4%, were willing to pay the same price ($3,000) in both scenarios. The rest expected an average discount of 58.3% for the surgery performed by an intelligent agent. Including people willing to pay the same price in both cases for scenario 1(*Q5)*, the average expected discount was 26.8%.

```
        Pearson's Chi-squared test

data:  dt$Q5 and dt$Q1
X-squared = 42.445, df = 8, p-value = 1.117e-06

                 Cohen w
                   0.217
```

Figure 7: Consumer Survey - Correlation Q1 & Q5 (Scenario 1)

Testing for the influence of AI, we used Pearson's Chi-squared test to find a significant influence at the 1% level. Using Cohen's W, we can conclude that AI knowledge (*Q1)* and the willingness to pay (*Q5*) the same price are low to moderately correlated (Bortz, 2010).

In scenario 2, participants were confronted with an investment scenario with the same fee structure PE uses. This means paying a 2% management fee and 20% carried interest. The expected returns were still outperforming the S&P 500 net of fees. 426 or 47.3% of all participants were willing to pay the same fees for a human or AI advisor. Again, AI knowledge and the willingness to pay the same fees (*Q7*) are moderately correlated (Bortz, 2010) at a 0.01 significance level. Looking at the frequencies participants with more AI knowledge have a higher willingness to pay the same fees (367/426 respondents who rated their knowledge > 2).

```
                Pearson's Chi-squared test

data:  dt$Q7 and dt$Q1
X-squared = 90.489, df = 4, p-value < 2.2e-16

                         Cohen w
                          0.3169
```

Figure 8: Consumer Survey - Correlation Q1 & Q7 (Scenario 2)

Due to the more complicated fee structure, we did not ask for expected discounts in scenario 2. Looking at more explanatory variables for the willingness to pay the same amount and, thus, the expected discount in perceived value creation by AI, we used a logistic and probabilistic model approach because of the binary nature of the dependent variable *Same Fees* in the investment scenario (Glonek & McCullagh, 1995).

Regressions

	Dependent variable:	
	Same_Fees	
	logistic	probit
	(1)	(2)
AI_Knowledge	0.488***	0.299***
	(0.069)	(0.042)
genderMale	0.330**	0.203**
	(0.144)	(0.088)
age	-0.016***	-0.010***
	(0.006)	(0.003)
platformiOS	-0.149	-0.087
	(0.152)	(0.093)
GBR	-0.365**	-0.229**
	(0.176)	(0.108)
GER	-0.311*	-0.195*
	(0.178)	(0.109)
Constant	-1.034***	-0.632***
	(0.377)	(0.231)
Observations	901	901
Log Likelihood	-569.492	-569.535
Akaike Inf. Crit.	1,152.984	1,153.070
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 9:Consumer Survey - Logistic and probabilistic regressions

Looking at both models, all variables besides *platformiOS*, and *GER*, the dummy variable for participants from Germany, are statistically significant, at least at the 0.05 level – the conventional significance threshold (Leppink et al., 2016). However, *GBR* and *GER* being negative implies a positive effect of being a US citizen on *Same_Fees*, which is the base case hidden in the constant. As the log-likelihood, representing the model-data fit, is very similar for both the logistic and probabilistic model, using either of the two is indifferent to the interpretation. We chose the logistic model for further operations.

To understand the size of the effect, the average marginal effects were computed:

```
Marginal Effects:
                 dF/dx    Std. Err.        z      P>|z|
AI_Knowledge  0.1215408  0.0172024  7.0654 1.602e-12 ***
genderMale    0.0819389  0.0356442  2.2988  0.021516 *
age          -0.0039597  0.0013729 -2.8842  0.003924 **
platformiOS  -0.0369929  0.0377331 -0.9804  0.326897
GBR          -0.0903265  0.0431095 -2.0953  0.036146 *
GER          -0.0770386  0.0436913 -1.7632  0.077859 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dF/dx is for discrete change for the following variables:

[1] "genderMale"  "platformiOS" "GBR"         "GER"
```

Figure 10: Consumer Survey - Marginal Effects

Holding all other variables constant, an increase in one unit of *AI Knowledge* will, on average, increase the probability of someone paying the same fees for AI investment decisions in scenario 2 by 12.2% at a significance level below .001. Being male also increases the probability by 8.2% at a .05 significance level, *ceteris paribus*. An increase in age by one unit and being from Great Britain decreases this probability by 0.4% at a .001 significance level and 9% at a .05 significance level, respectively.

When asked whether participants support their pensions being invested in PE funds that extensively use AI, 44% either support (31.1%) or strongly support (12.9%) this. 35% have a neutral opinion and 21% do not support it. Additionally, consumers were confronted with three questions that experts were asked. Namely: “An AI recommends firing a significant part of the workforce to increase profitability. Would you?” (*Question 9*), “Do you think a future where AI makes major decisions without human oversight is plausible?” (*Question 10*) and "Should humans have a discretionary override?".

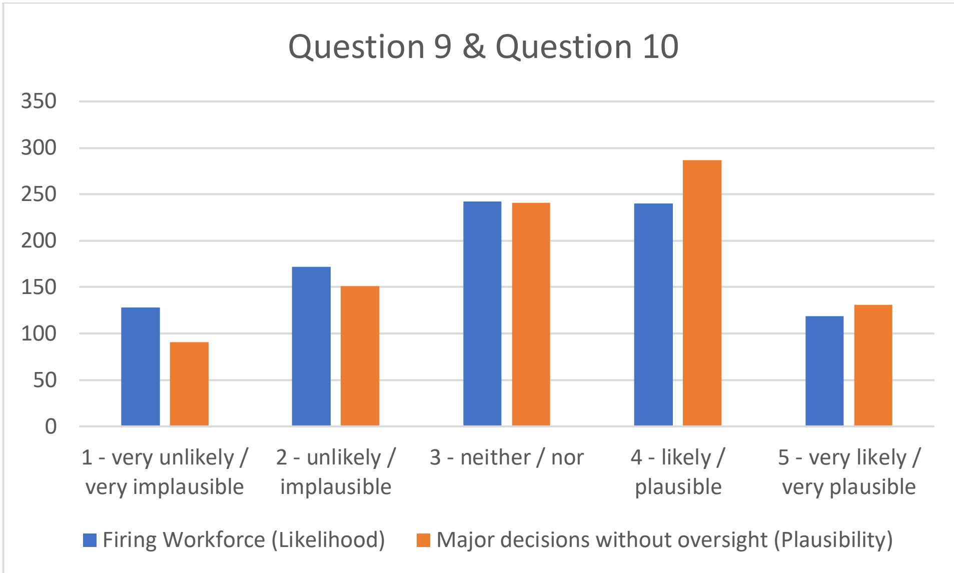

Figure 11: Consumer Survey - Likert Scale Q9 & Q10

As shown in Figure 11, 54.5% of participants, which excludes 242 consumers who voted neither/nor, are more likely to follow through with the recommendation. Using the chi-squared test and Cohen w, one can see that these findings are moderately correlated with knowledge about AI (*Q1*) at a 0.01 significance level. Consumer responses significantly contrast with expert opinions on this topic.

```
        Pearson's Chi-squared test

data:  dt$Q1 and dt$Q9
X-squared = 408.26, df = 16, p-value < 2.2e-16

                Cohen w
                 0.6731
```

Figure 12: Consumer Survey - Correlation Q1 & Q9

The answers regarding the plausibility of future major decisions being made by AI without human oversight follow a similar pattern but are slightly more skewed towards it being plausible. Although many more thought it is plausible, only 174 (19.3%) participants considered it a good idea. Seven hundred and twenty-seven, or 80.6% of all participants, believed that humans should always have a discretionary override over AI decisions.

Discussion

This chapter is split in two parts. The first is a general discussion of our findings, whereas the second one explores potential future scenarios and their influence on PE AI.

General Discussion

Most experts agreed that AI is the biggest disruptor in business today. Other results indicated slow adoption with the potential for radical changes for PE internally and the capacity for portfolio company value creation. AI can be classified as disruptive innovation and a source of competitive advantage for PE. Thus, one might conclude that PE AI is an emergent core competency currently in a state of disruptive innovation. It can be an excellent lever for GPs to keep returns steady, which is important as the recent trend of democratization and the consumer sentiment towards the current fee structure demonstrate. We also showed that consumers are open towards PE AI.

Expanding the scope beyond GP value creation to portfolio company value creation, our evidence suggested a **positive influence of PE on companies trying to develop and implement AI capabilities**. Table 6 shows identified levers, including strategic guidance, cross-industry expertise, the provision of critical resources, and management alignment. Strategic guidance and management alignment are essential, as often AI initiatives are not properly managed and then become treated as side projects before finally being written off by management. PE can help identify use cases, correct AI methods, and provide the management team with insights on why using AI would be beneficial. This counters lack of understanding of the technology. Additionally, PE can alleviate financial constraints that have inhibited costly AI initiatives. By providing cross-industry expertise, they can also help companies navigate emergent phenomena, such as risks, while implementing deliberate strategy.

Challenges	PE capabilities to minimize them
Ethical and Legal	• Provide resources for addressing data privacy and security • Leverage network and expertise to ensure compliance with regulations • Assisting in hiring experts for ethical concerns and legal implications
Data	• Pool and share data across portfolio companies to reinforce models • Utilize resources and network to acquire high-quality data • Means to invest in data infrastructure for better data availability and quality
Trustworthiness and Explainability	• Facilitate transparency by ensuring management buy-in and support • Use industry expertise to help implement best practices to build trust in AI systems • Provide resources for research and development of explainable AI
Cultural and Understanding	• Offer strategic guidance and expertise to promote AI adoption • Address fears of job loss and cultural change through education and communication • Ensure management support for AI integration and the necessary cultural shift → ownership concentration and incentive alignment • Facilitate management practices that are aligned with integrating AI strategy into business strategy
Other	• Tackle high costs of AI development by providing funding, resources, and streamlining the process • Address talent shortages by leveraging networks to hire skilled data scientists and AI experts • Offer expertise in identifying and capitalizing on AI use cases • Evade common pitfalls through cross-industry expertise

Table 4: AI Challenges & PE Capabilities

Moreover, having access to expert networks can also reduce the impact of current talent shortages for portfolio companies. However, not all challenges can be solved by PE AI. Data quality remains an issue, as does data availability. Although some experts mentioned the possibility of sharing data across portfolio companies to reinforce and adjust their models, several AI experts questioned viability as this depends on the industry businesses operate in. Thus, it needs to be evaluated on a case-by-case basis. Ultimately, it boils down to whether the fund is better equipped than the company itself. This is likely the case for many prime targets of buyout funds, namely mature and well-established companies that are not used to data-centric culture. However, the advantages will likely decline or be nonexistent for AI-native companies. Also, PE funds must focus on developing core AI competencies to leverage their advantages when applying AI in portfolio companies.

Scenario Planning

Due to the hype associated with AI and novel niche domain of PE AI, its future is highly dependent on various factors. Based on the literature examined and expert interviews we identified two essential factors that could influence the notion of PE AI significantly: the adoption of AI in business and its regulation. Thus, the commonly accepted 2 x 2 matrix method is used to showcase possible future scenarios that could facilitate or dampen PE AI (Ramirez & Wilkinson, 2014). We have analyzed the factors' influence on PE AI's competitive advantage, AI Innovation, and Risks and Challenges associated with AI according to our findings and the literature. Additionally, we have identified the most likely and most favorable scenario.

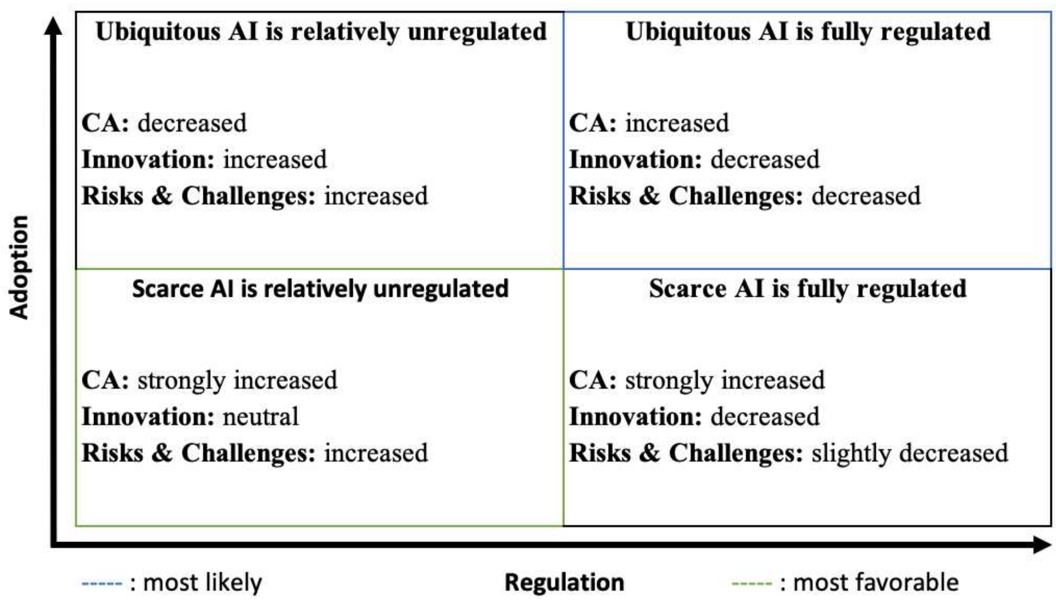

Figure 13: Scenario Planning

Ubiquitous AI is Relatively Unregulated

Competitive Advantage: The Competitive advantage for PE AI may decrease due to the widespread adoption of AI across industries. As AI becomes more accessible (lower costs & higher availability of models) other firms may also be able to leverage AI, narrowing the gap between PE AI and non-backed competitors. However, PE may create excess value in managing the increased risks and challenges.

Innovation: A low regulatory environment could enable PE to leverage cutting-edge AI technologies more quickly, allowing them to drive innovation, efficiency, and subsequently higher returns.

Risks & Challenges: The lack of regulation might lead to higher uncertainty and a more risk-prone environment. Algorithmic biases, security vulnerabilities, and systemic risks might be amplified. Additionally, these risks could cause ethical and social concerns which could result in a negative public perception, backlash from stakeholders, and potential future regulatory actions.

Ubiquitous AI is Fully Regulated

Competitive Advantage: PE firms can navigate the high regulatory environment with expertise and their inherent resources, giving them the opportunity to create competitive advantage for their portfolio companies. Also, PEs can help them avoid legal risks and penalties, leading to increased value creation.

Innovation: The adoption and implementation of cutting-edge AI may slow down, as companies need to comply with strict rules and guidelines. This could potentially affect growth opportunities and return on investments.

Risks & Challenges The strict regulation may mitigate AI associated risks, such as biases, security concerns, and systemic risks. Ethical and social concerns are likely to be covered by regulation, resulting in a more responsible AI ecosystem. PE AI could benefit by minimized negative public perception and consumer openness to AI initiatives as these are commonly known and accepted due to decreased negative externalities.

This scenario is the most likely one as AI is a top-of-mind topic for many businesses and consumers. Also, European regulators are currently revising the EU AI Act which will emphasize trustworthiness and excellence in AI and set strict regulations for models. This is also consonant with findings from the literature review.

Scare AI is Relatively Unregulated

Competitive Advantage: PE AI would have a significant competitive advantage over others due to the limited availability of AI. PE can freely use AI to generate excess value in their portfolio company. Increased risks could also be a lever to generate alpha if PE firms can proactively manage risks and protect their investments.

Innovation: While loose regulation can facilitate AI innovation, the innovation could be limited to narrow use cases where the select actors with AI access see the need. Additionally, it could create a large gap between companies with and without AI.

Risks & Challenges: The low regulatory environment could heighten risks and actors with AI access could potentially face public scrutiny and pressure to address risks and ethical concerns despite the absence of regulation.

This scenario would be the most favorable for PE AI. PEs with access and required capabilities to AI as limited resource could create significant competitive advantages as other companies without access could not implement this efficient technology.

Scarce AI is Fully Regulated

Competitive Advantage: PEs with access to AI and the ability to navigate complex regulations would have a significant competitive advantage over others. The limited availability could make AI a highly valuable asset, and PE firms could use their access to drive innovation and efficiencies in their portfolio company, leading to greater value creation.

Innovation: The strict regulation and limited availability may slow down adoption and implementation of AI. Thus, creating a more significant gap between companies with AI access and those without.

Risks & Challenges: The high regulatory environment may mitigate AI associated risks, giving PE AI the opportunity to focus on value creation. However, the limited availability could exacerbate ethical and social concerns as it may create a divide between companies with and without access to AI.

Conclusion and Limitations

Conclusion

In synthesizing our findings, we employed a triangulation approach, merging insights from the literature review, expert interviews, and consumer survey. This methodology facilitated a comprehensive understanding of how private equity (PE) uses artificial intelligence (AI) for improving capabilities in portfolio companies thereby creating value.

Our findings highlight the advantages PE AI brings to the table. As a strategic catalyst, PE delivers invaluable guidance, enabling portfolio companies to navigate the complex AI landscape effectively. By providing cross-industry expertise and access to resources, PE firms can identify AI use cases and empower businesses to overcome financial and talent constraints to implement them. Moreover, the unique ownership structure of PE-backed companies ensures top-down alignment and commitment from management teams, fostering successful integration of AI initiatives. This support prevents AI projects from being sidelined or neglected, instead, embedding them into the very fabric of the organization. Nevertheless, it's crucial to recognize that PE's ability to create value may vary depending on a firm’s AI maturity. While mature and well-established businesses often benefit from PE's guidance, AI-native firms might not experience the same level of advantage. Additionally, with regulators emphasizing trustworthiness and regulation (EU AI Act) and the current democratization of AI, PEs need to ensure to keep their competitive advantage when it comes to deploying AI in portfolio companies.

Our study also indicated that consumers are open to PE AI; however, they expect slight discounts for value creation derived from AI implementations. This finding underscores the importance of striking a balance between harnessing AI's potential and managing consumer expectations.

In conclusion, our triangulation approach illuminated the significant value creation of private equity when deploying AI in portfolio companies. By leveraging PE's strategic guidance, expertise, resources, and alignment, businesses can harness the transformative potential of AI and thrive in an increasingly competitive landscape.

Limitations

Research on the impact of a novel, not yet mature technology on a niche business domain operating in a complex system is associated with significant uncertainty. Thus, further AI advances, such as a commoditized availability mentioned by one expert, could diminish the impact of PE as an idiosyncratic source of alpha. Moreover, just like most forms of investment, PE is heavily influenced by macroeconomic factors. Nowadays the changing macro environment with high inflation and interest rates could influence possible advantages that PE-backed companies have over their peers.

A novel topic also means that the analysis only presents a snapshot, because no time-series data for different vintages of funds applying AI to their portfolio companies is available. Given the common holding period of portfolio companies, no large-scale quantitative data is available since funds have only recently started deploying AI.

Additionally, PE experts might have exhibited confirmation biases as all of them already had exposure to AI. This, added to the small sample size, suggests that results might not be representative and are skewed by personal attitudes.

Although we used a panel with a national representative quota for the consumer survey, the limited penetration of the panel in the US market might have led to a selection bias in the US sample. Further, we asked participants to give a self-assessment of their AI knowledge which might not be completely accurate when compared to AI experts -- this is probably more serious at the high end of the scale (5 – very knowledgeable). People with low expertise tend to overestimate their knowledge (Dunning, 2011).

Further Research

Further research is necessary to support our initial findings concerning PE and AI. As the typical holding period of 5-10 years is still ongoing for any vintages actively deploying AI for value creation, we could not perform a quantitative assessment of the impact. Thus, quantitative assessment of PE AI's impact on portfolio companies is essential to prove value creation.

Additionally, analyzing non-data-centric mature companies developing and implementing AI might be valuable to contrast these findings with PE-backed AI.

Lastly, the study of potential barriers and ethical considerations in AI adoption, as well as the development of industry-specific AI strategies for PE, can contribute to a fuller understanding of the interplay between PE and AI.

References

Acharya, V. V., Gottschalg, O. F., Hahn, M., & Kehoe, C. (2012). Corporate Governance and Value Creation: Evidence from Private Equity. *Review of Financial Studies*, *26*(2), 368–402. https://doi.org/10.1093/rfs/hhs117

Astebro, T. B. (2021). An Inside Peek at AI Use in Private Equity. *The Journal of Financial Data Science*, *3*(3), 97–107. https://doi.org/10.3905/jfds.2021.1.067

Axelson, U., Jenkinson, T., Strömberg, P., & Weisbach, M. S. (2013). Borrow Cheap, Buy High? The Determinants of Leverage and Pricing in Buyouts. *Journal of Finance*, 68(6), 2223–2267. https://doi.org/10.1111/jofi.12082

Bain. (2022). *Global Private Equity Report 2022*.

Baker, K. H., Filbeck, G., & Kiymaz, H. (2015). *Private Equity: Opportunities and Risks (Financial Markets and Investments)* (1st ed.). Oxford University Press.

Barney, J. B. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barreto, I. (2010). Dynamic Capabilities: A Review of Past Research and an Agenda for the Future. *Journal of Management*, *36*(1), 256–280. https://doi.org/10.1177/0149206309350776

Barriball, K., & While, A. (1994). Collecting data using a semi-structured interview: a discussion paper. *Journal of Advanced Nursing*, *19*(2), 328–335. https://doi.org/10.1111/j.1365-2648.1994.tb01088.x

Bean, R. (2019, January 25). Why fear of disruption is driving investment in AI. *MIT Sloan Management Review*.

Ben-Zvi, T., & Luftman, J. (2021). IT after the Coronavirus Pandemic: Back to Normal? In *AMCIS 2021 Proceedings*. https://aisel.aisnet.org/amcis2021/strategic_is/strategic_is/3

Bertalanffy, L. V. (1968). *General system theory: Foundations, development, applications*. G. Braziller.

Bernstein, S., & Sheen, A. (2013). The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2336672

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital Business Strategy: Toward a Next Generation of Insights. *MIS Quarterly*, *37*(2), 471–482. https://doi.org/10.25300/misq/2013/37:2.3

Bikhchandani, S., & Sharma, S. (2000). Herd Behavior in Financial Markets. *Imf Staff Papers*, *47*(3), 279–310. https://doi.org/10.2307/3867650

Blackrock. (2019). *Artificial intelligence and machine learning in asset management*. https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-artificial-intelligence-machine-learning-asset-management-october-2019.pdf

Bloom, N., Sadun, R., & Van Reenen, J. (2015). Do Private Equity Owned Firms Have Better Management Practices? *American Economic Review*, *105*(5), 442–446. https://doi.org/10.1257/aer.p20151000

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Bortz, J., & Schuster, C. (2010). Statistik für Human- und Sozialwissenschaftler. *Springer-Lehrbuch*. https://doi.org/10.1007/978-3-642-12770-0

Boucly, Q., Sraer, D., & Thesmar, D. (2011). Growth LBOs. *Journal of Financial Economics*, *102*(2), 432–453. https://doi.org/10.1016/j.jfineco.2011.05.014

Braun, R., Jenkinson, T., & Stoff, I. (2017). How persistent is private equity performance? Evidence from deal-level data. *Journal of Financial Economics*, *123*(2), 273–291. https://doi.org/10.1016/j.jfineco.2016.01.033

Brown, G., Harris, B., Jenkinson, T., Kaplan, S., & Robinson, D. (2020). Private Equity: Accomplishments and Challenges. *Journal of Applied Corporate Finance*, *32*(3), 8–20. https://doi.org/10.1111/jacf.12415

Brown, G. W., & Kaplan, S. N. (2019). Have Private Equity Returns Really Declined? *The Journal of Private Equity*, *22*(4), 11–18. https://doi.org/10.3905/jpe.2019.1.087

Brynjolfsson, E., & McAfee, A. P. (2017). Artificial intelligence, for real. *Harvard Business Review*. https://starlab-alliance.com/wp-content/uploads/2017/09/AI-Article.pdf

Buchner, A. (2016). Dealing with non-normality when estimating abnormal returns and systematic risk of private equity: A closed-form solution. *Journal of International*

Financial Markets, Institutions and Money, *45*, 60–78. https://doi.org/10.1016/j.intfin.2016.06.001

Calzolari, G. (2021). *Artificial Intelligence market and capital flows*. European Parliament. https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662912/IPOL_STU(2021)662912_EN.pdf

Carroll, A. (2022, April 1). How AI could unlock opportunities in PE. *Private Equity International*. https://www.privateequityinternational.com/how-ai-could-unlock-opportunities-in-pe/

Caswell, I., & Bapna, A. (2022, May 11). Unlocking Zero-Resource Machine Translation to Support New Languages in Google Translate. *Google Research Blog*. https://ai.googleblog.com/2022/05/24-new-languages-google-translate.html

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business School Press.

Christensen, C. M., & Overdorf, M. (2000). Meeting the Challenge of Disruptive Change. *Harvard Business Review*, *78*(2), 66–77.

Cohn, J. A., Nestoriak, N., & Wardlaw, M. (2016). How Do Employees Fare in Leveraged Buyouts? Evidence from Workplace Safety Records. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2728704

Cohn, J. A., Nestoriak, N., & Wardlaw, M. (2021). Private Equity Buyouts and Workplace Safety. *Review of Financial Studies*, *34*(10), 4832–4875. https://doi.org/10.1093/rfs/hhab001

Cohn, J. B., Hotchkiss, E. S., & Towery, E. M. (2022). Sources of Value Creation in Private Equity Buyouts of Private Firms. *Review of Finance*, *26*(2), 257–285. https://doi.org/10.1093/rof/rfac005

Cohn, J. B., & Wardlaw, M. I. (2016). Financing Constraints and Workplace Safety. *The Journal of Finance*, *71*(5), 2017–2058. https://doi.org/10.1111/jofi.12430

Collins, R. (2022). *The future of PE's democratisaiton*. Partners Group. https://www.partnersgroup.com/fileadmin/user_upload/Files/News_Views_PDFs/20220503_PEI_Future_of_PE_Partners_Group_VFinal.pdf

Cornelius, P. K. (2011). *International Investments in Private Equity: Asset Allocation, Markets, and Industry Structure*. Academic Press.

Dadteev, K., Shchukin, B. A., & Nemeshaev, S. (2020). Using artificial intelligence technologies to predict cash flow. *Procedia Computer Science*, *169*, 264–268. https://doi.org/10.1016/j.procs.2020.02.163

Dastin, J. (2018, October 11). *Amazon scraps secret AI recruiting tool that showed bias against women*. Reuters. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

Davenport, T. H., & Mahidhar, V. (2018). What's your cognitive strategy. *MIT Sloan Management Review*, *59*(4), 19–23. https://sloanreview.mit.edu/article/whats-your-cognitive-strategy/

Davis, S. J., Haltiwanger, J., Handley, K., Lipsius, B., Lerner, J., & Miranda, J. (2021). The Economic Effects of Private Equity Buyouts. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3465723

De Beer, H. (2023, February 1). *What is democratisation?* Private Equity International. https://www.privateequityinternational.com/what-is-democratisation/

Deloitte. (2021). *Becoming an A-fueled organization*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/technology/us-ai-institute-effective-ai-strategy-new.pdf

Dunning, D. (2011). The Dunning–Kruger Effect. *Elsevier EBooks*, 247–296. https://doi.org/10.1016/b978-0-12-385522-0.00005-6

Eaton, C., Howell, S. T., & Yannelis, C. (2020). When Investor Incentives and Consumer Interests Diverge: Private Equity in Higher Education. *Review of Financial Studies*. https://doi.org/10.3386/w24976

Farman, M. (2023, February). *2023 outlook: HarbourVest co-CEO predicts challenging conditions*. Private Equity International.

Fracassi, C., Previtero, A., & Sheen, A. (2017). Is Private Equity Good for Consumers? *Social Science Research Network*. https://doi.org/10.2139/ssrn.2911387

Fracassi, C., Previtero, A., & Sheen, A. (2022). Barbarians at the Store? Private Equity, Products, and Consumers. *Journal of Finance*, 77(3), 1439–1488. https://doi.org/10.1111/jofi.13134

Fraser-Sampson, G. (2010). *Private Equity as an Asset Class* (2nd ed.). Wiley.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2021). Predictably Unequal? The Effects of Machine Learning on Credit Markets. *Journal of Finance*, *77*(1), 5–47. https://doi.org/10.1111/jofi.13090

Gambacorta, L., Huang, Y., Qiu, H., & Wang, J. (2019). *How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm*. Bank for International Settlements. https://www.bis.org/publ/work834.pdf

Garcia Gomez, P., Maug, E. G., & Obernberger, S. (2020). Private Equity Buyouts and Employee Health. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3601813

Gensler, G., & Bailey, L. (2020). Deep Learning and Financial Stability. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3723132

Geronimo, A. (2022, March 11). *AI start-ups attracted the largest number of VC investors in 2021*. ITP.net. https://www.itp.net/business/ai-start-ups-attracted-the-largest-number-of-vc-investors-in-2021-report

Glonek, G. F. V., & McCullagh, P. (1995). Multivariate Logistic Models. *Journal of the Royal Statistical Society Series B-Methodological*, *57*(3), 533–546. https://doi.org/10.1111/j.2517-6161.1995.tb02046.x

Gompers, P., Kaplan, S. N., & Mukharlyamov, V. (2016). What do private equity firms say they do? *Journal of Financial Economics*, *121*(3), 449–476. https://doi.org/10.1016/j.jfineco.2016.06.003

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Gredil, O. R., Griffiths, B., & Stucke, R. (2023). Benchmarking private equity: The direct alpha method. *Journal of Corporate Finance*, 102360. https://doi.org/10.1016/j.jcorpfin.2023.102360

Guo, S., Hotchkiss, E. S., & Song, W. (2011). Do Buyouts (Still) Create Value? *The Journal of Finance*, *66*(2), 479–517. https://doi.org/10.1111/j.1540-6261.2010.01640.x

Gupta, A., Howell, S. T., Yannelis, C., & Gupta, A. (2020). Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3537612

Haller, B., & Campbell, K. (2022). *Future of Diligence*. West Monroe. https://www.westmonroe.com/perspectives/signature-research/future-of-diligence-in-private-equity

Harris, R. S., Jenkinson, T., Kaplan, S. A., & Stucke, R. (2020). Has Persistence Persisted in Private Equity? Evidence from Buyout and Venture Capital Funds. *Social Science Research Network*. https://doi.org/10.3386/w28109

Harris, R. S., Jenkinson, T., & Kaplan, S. N. (2014). Private Equity Performance: What Do We Know? *The Journal of Finance*, *69*(5), 1851–1882. https://doi.org/10.1111/jofi.12154

Higson, C., & Stucke, R. (2012). The Performance of Private Equity. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2009067

Holloway, C. (1983). Strategic management and artificial intelligence. *Long Range Planning*, *16*(5), 89–93. https://doi.org/10.1016/0024-6301(83)90082-1

Hossain, N. U. I., Dayarathna, V. L., Nagahi, M., & Jaradat, R. (2020). Systems Thinking: A Review and Bibliometric Analysis. *Systems*, *8*(3), 23. https://doi.org/10.3390/systems8030023

Hu, K. (2023, February 1). *ChatGPT sets record for fastest-growing user base - analyst note.* Reuters. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Huang, Z. (2022, August 8). *Baidu Wins Approval for China's First Full Driverless Taxis*. Bloomberg.com. https://www.bloomberg.com/news/articles/2022-08-08/baidu-wins-approval-for-china-s-first-full-driverless-taxis

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World*. Harvard Business Review Press.

International Finance Corporation. (2020). *MYBank's gender-driven approach to lending*. https://www.ifc.org/wps/wcm/connect/3e0cfba8-12c9-42fe-943b-e99f4a36de73/202008_D2E_MyBank.pdf?MOD=AJPERES&CVID=nfvyYCR

Intertrust. (2018). *Private Equity*. https://www.intertrustgroup.com/wp-content/uploads/2021/02/Private-equity.pdf

Ivanov, S. H., & Webster, C. (2017). Adoption of Robots, Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies – A Cost-Benefit Analysis. *Social Science Research Network*. https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3007577_code657096.pdf?abstractid=3007577&mirid=1

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, *76*(2), 323–329. https://econpapers.repec.org/article/aeaaecrev/v_3a76_3ay_3a1986_3ai_3a2_3ap_3a323-29.htm

Kahneman, D., Sibony, O., & Sunstein, C. R. (2021). *Noise*. HarperCollins UK.

Kaplan, S. N., & Schar, A. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. *The Journal of Finance*, *60*(4), 1791–1823. https://doi.org/10.1111/j.1540-6261.2005.00780.x

Kaplan, S. N., & Strömberg, P. (2009). Leveraged Buyouts and Private Equity. *Journal of Economic Perspectives*, *23*(1), 121–146. https://doi.org/10.1257/jep.23.1.121

Kavlakoglu, E. (2020, May 27). *AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the Difference?* IBM Artificial Intelligence Blog. https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks

Keasey, K., Pindado, J., & Rodrigues, L. (2015). The determinants of the costs of financial distress in SMEs. *International Small Business Journal*, *33*(8), 862–881. https://doi.org/10.1177/0266242614529317

Kuhlmann, M. (2014). Explaining Financial Markets in Terms of Complex Systems. *Philosophy of Science*, *81*(5), 1117–1130. https://doi.org/10.1086/677699

Langenbucher, K. (2020). Responsible AI-based credit scoring–a legal framework. *European Business Law Review*, *31*(4), 527–572. https://doi.org/10.54648/eulr2020022

Le, A. (2023, February 1). *How does democratisation affect GP-LP alignment?* Private Equity International. https://www.privateequityinternational.com/how-does-democratisation-affect-gp-lp-alignment/

Le Nadant, A. L., Perdreau, F., & Bruining, H. (2018). Industry specialization of private equity firms: a source of buy-out performance heterogeneity. *Venture Capital*, *20*(3), 237–259. https://doi.org/10.1080/13691066.2017.1422424

LeCun, Y., Bengio, Y., & Hinton, G. E. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Leppink, J., Winston, K., & O'Sullivan, P. S. (2016). Statistical significance does not imply a real effect. *Perspectives on Medical Education*, *5*(2), 122–124. https://doi.org/10.1007/s40037-016-0256-6

Lichtenthaler, U. (2019). An Intelligence-Based View of Firm Performance: Profiting from Artificial Intelligence. *Journal of Innovation Management* (Vol. 7, Issue 1, pp. 7–20). University of Porto. https://doi.org/10.24840/2183-0606_007.001_0002

Lin, J., Stienen, M. N., Prather, B., & Gammie, C. F. (2020). Feature Extraction on Synthetic Black Hole Images. *ArXiv (Cornell University)*. https://arxiv.org/pdf/2007.00794.pdf

Lissitz, R. W., & Green, S. B. (1975). Effect of the number of scale points on reliability: A Monte Carlo approach. *Journal of Applied Psychology*, *60*(1), 10–13. https://doi.org/10.1037/h0076268

Ljungqvist, A., & Richardson, M. P. (2003). The Cash Flow, Return and Risk Characteristics of Private Equity. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.369600

Luftman, J. (n.d.). *IT-Business Alignment and the Evolving Role of the CIO and IT: 2017-18 Trends and Projections.* https://www.researchgate.net/profile/Rajeev-Dwivedi-Phd/publication/283214076_Influential_IT_management_trends_an_international_study/links/5e5639bc92851cefa1c494a0/Influential-IT-management-trends-an-international-study.pdf

Luftman, J., Lyytinen, K., & Zvi, T. B. (2017). Enhancing the measurement of information technology (IT) business alignment and its influence on company performance. *Journal of Information Technology*, *32*(1), 26–46. https://doi.org/10.1057/jit.2015.23

Marvel, M. R., & Lumpkin, G. T. (2007). Technology Entrepreneurs' Human Capital and Its Effects on Innovation Radicalness. *Entrepreneurship Theory and Practice*, *31*(6), 807–828. https://doi.org/10.1111/j.1540-6520.2007.00209.x

Mayring, P. (2014). Qualitative content analysis: theoretical foundation, basic procedures and software solution. https://nbn-resolving.org/urn:nbn:de:0168-ssoar-395173

McCarthy, J. (2007). *What is Artificial Intelligence*. Stanford University. http://www-formal.stanford.edu/jmc/whatisai.pdf

McKinsey. (2022). Private markets rally to new heights - McKinsey Global Private Markets Review 2022.

https://www.mckinsey.com/~/media/mckinsey/industries/private%20equity%20and%20principal%20investors/our%20insights/mckinseys%20private%20markets%20annual%20review/2022/mckinseys-private-markets-annual-review-private-markets-rally-to-new-heights-vf.pdf

Mendoza, C. (2022, September 28). *Blackstone Strategic Partners: 'Democratization is not a matter of if, but when.'* Private Funds CFO. https://www.privatefundscfo.com/blackstone-strategic-partners-democratisation-is-not-a-matter-of-if-but-when/

Mendoza, C. (2023a, March 6). *Blackstone launches branding push to attract non-institutional investors*. Private Equity International. https://www.privateequityinternational.com/blackstone-launches-branding-push-to-attract-non-institutional-investors/?utm_source=newsletter-alert&utm_medium=email&utm_campaign=pei-alert&utm_content=06-03-2023

Mendoza, C. (2023b, February). *Capital Call Slowdown: Wellcome Trust's PE portfolio turns cashflow-negative*. Private Equity International.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mintzberg, H., & Waters, J. K. (1985). Of strategies, deliberate and emergent. *Strategic Management Journal*, 6(3), 257–272. https://doi.org/10.1002/smj.4250060306

Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill Science/Engineering/Math.

Murphy, K. P. (2022). *Probabilistic Machine Learning: An Introduction*. MIT Press.

Obernberger, S. (2022). Human Capital Risk in Private Equity. *Social Science Research Network*. https://doi.org/10.2139/ssrn.4227954

ODSC. (2022, August 18). *Meta's BlenderBot 3 AI Chatbot is Already Spewing Controversial Statements*. https://opendatascience.com/metas-blenderbot-3-ai-chatbot-is-already-spewing-controversial-statements/

OECD. (2021). *Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers*. https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf

Ohno, T., & Bodek, N. (1988). *Toyota Production System: Beyond Large-Scale Production* (1st ed.). Productivity Press.

Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., & Lekakos, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. *Information Systems and E-Business Management*, *16*(3), 479–491. https://doi.org/10.1007/s10257-018-0377-z

Phalippou, L. (2008). The Hazards of Using IRR to Measure Performance: The Case of Private Equity. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1111796

Phalippou, L. (2013). Performance of Buyout Funds Revisited?*. *Review of Finance*, *18*(1), 189–218. https://doi.org/10.1093/rof/rft002

Point72 Hyperscale. (2023). Overview. https://point72hyperscale.com/

Porter, M. E. (1996). What Is Strategy? Harvard Business Review. https://hbr.org/1996/11/what-is-strategy

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. *Harvard Business Review*. https://hbr.org/1985/07/how-information-gives-you-competitive-advantage

Pradhan, R., Weech-Maldonado, R., Harman, J. S., Al-Amin, M., & Hyer, K. (2014). Private Equity Ownership of Nursing Homes: Implications for Quality. *Journal of Health Care Finance*, *42*(2). https://www.healthfinancejournal.com/index.php/johcf/article/download/12/15

Prahalad, C. K., & Hamel, G. (2009). The Core Competence of the Corporation. *Social Science Research Network*, 21–40. https://doi.org/10.4324/9780080517889-6

PwC. (2017). *Sizing the prize*. https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf

PwC. (2022). *2022 AI Business Survey*. https://www.pwc.com/us/en/tech-effect/ai-analytics/ai-business-survey.html

Ramirez, R., & Wilkinson, A. (2014). Rethinking the 2×2 scenario method: Grid or frames? *Technological Forecasting and Social Change*, 86, 254–264. https://doi.org/10.1016/j.techfore.2013.10.020

Raso, F., Hilligoss, H., Krishnamurthy, V., Bavitz, C., & Kim, L. Y. (2018). Artificial Intelligence & Human Rights: Opportunities & Risks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3259344

Rimol, M., & Costello, K. (2021, March 10). *Gartner Says Tech Investors Will Prioritize Data Science and Artificia*. Gartner. https://www.gartner.com/en/newsroom/press-releases/2021-03-10-gartner-says-tech-investors-will-prioritize-data-science-and-artificial-intelligence-above-gut-feel-for-investment-decisions-by-20250

Rubinstein, M. P. (1973). The Fundamental Theorem of Parameter-Preference Security Valuation. *Journal of Financial and Quantitative Analysis*, *8*(1), 61. https://doi.org/10.2307/2329748

Rueßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015, April 9). *Industry 4.0: The future of productivity and growth in manufacturing industries*. Boston Consulting Group. https://www.bcg.com/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries

Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach, Global Edition*.

Schmid, T., Hildesheim, W., Holoyad, T., & Schumacher, K. (2021). The AI Methods, Capabilities and Criticality Grid. *Ki - Künstliche Intelligenz*, *35*(3–4), 425–440. https://doi.org/10.1007/s13218-021-00736-4

Shao, Z. (2019). Interaction effect of strategic leadership behaviors and organizational culture on IS-Business strategic alignment and Enterprise Systems assimilation. *International Journal of Information Management*, *44*, 96–108. https://doi.org/10.1016/j.ijinfomgt.2018.09.010

Skolnik, O., Habbel, M., Rainey, B., De Mol, A., & Ramaswami, I. (2023, February 27). *Why Private Equity Is Targeting Individual Investors*. Bain & Company. https://www.bain.com/insights/why-private-equity-is-targeting-individual-investors-global-private-equity-report-2023/

Sorensen, M., & Jagannathan, R. (2015). The Public Market Equivalent and Private Equity Performance. *Financial Analysts Journal*, *71*(4), 43–50. https://doi.org/10.2469/faj.v71.n4.4

Stahl, B. C., & Wright, D. (2018). Ethics and Privacy in AI and Big Data: Implementing Responsible Research and Innovation. *IEEE Security &Amp; Privacy*, *16*(3), 26–33. https://doi.org/10.1109/msp.2018.2701164

Statista. (2023). *Number of people with wealth over one million U.S dollars 2021, by country*. https://www.statista.com/statistics/268411/countries-with-the-most-millionaires/

Stokes, J., Yang, K., Swanson, K. L., Jin, W., Cubillos-Ruiz, A., Donghia, N. M., MacNair, C. R., French, S., Carfrae, L. A., Bloom-Ackermann, Z., Tran, V., Chiappino-Pepe, A., Badran, A. H., Andrews, I., Chory, E. J., Church, G. M., Brown, E. D., Jaakkola, T. S., Barzilay, R., & Collins, J. J. (2020). A Deep Learning Approach to Antibiotic Discovery. *Cell*, *180*(4), 688-702.e13. https://doi.org/10.1016/j.cell.2020.01.021

Teece, D. J., Pisano, G. P., & Shuen, A. (1990). Firm capabilities, resources and the concept of strategy. Berkeley, Calif.

Teece, D. J., Pisano, G. P., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Thormundsson, B. (2022). *AI corporate investment worldwide 2015-2021*. Statista. https://www.statista.com/statistics/941137/ai-investment-and-funding-worldwide/

Turner, D. (2010). Qualitative Interview Design: A Practical Guide for Novice Investigators. *The Qualitative Report*. https://doi.org/10.46743/2160-3715/2010.1178

U.S. Senate. (2022). *Retirement Savings Modernization Act* (WIL22269 1R6). Senate of the United States. https://www.banking.senate.gov/imo/media/doc/retirement_savings_modernization_act.pdf

Venkatraman, V. (2017). *The Digital Matrix: New Rules for Business Transformation Through Technology.*

Vincent, J. (2016, May 24). *Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day*. The Verge. https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist

Vroomen, P., & Desa, S. (2016). An intelligent decision support system for private equity investment. *Future Technologies Conference*. https://doi.org/10.1109/ftc.2016.7821631

IBM. (n.d.). *What is Strong AI?*. https://www.ibm.com/topics/strong-ai

Yeow, A., Soh, C., & Hansen, R. (2018). Aligning with new digital strategy: A dynamic capabilities approach. *The Journal of Strategic Information Systems*, *27*(1), 43–58. https://doi.org/10.1016/j.jsis.2017.09.001

Zou, J., & Schiebinger, L. (2018). AI can be sexist and racist — it's time to make it fair. *Nature*, *559*(7714), 324–326. https://doi.org/10.1038/d41586-018-05707-8

Appendices

Appendix A : Interview Questions : PE Experts

Topic	Question
General	How long have you been working in PE?
Value creation in PE	How do you define value creation in PE?
	How do you measure it?
Internal use of AI	How are you applying AI internally?
	What are your plans with AI in the future?
	How will AI affect the industry?
AI in portfolio companies	Since when have you been applying AI to your portfolio companies?
	What advantages do your portfolio companies have when applying AI compared to their non-backed peers?
Systemic risks	Is it possible that AI leads to phenomenon such as herding behavior?
Attitudes towards AI	Likert-Scale: AI is the biggest disruptor in today's business world.
	Likert-Scale: An AI recommends firing a significant part of the workforce, would you?
	Do you think a future where AI makes major decisions without human oversight is plausible?
	Should humans have a discretionary override?

Table 5: Interview Questions - PE Experts

Appendix B : Interview Questions : AI Experts

General	How many years of experience do you have with AI?
AI value creation & challenges	How can AI create value for companies?
	What are major challenges for businesses trying to develop and implement AI?
PE AI	How could a PE fund create value by enabling AI in its portfolio companies?
Systemic risk	Is it possible that AI leads to phenomenon such as herding behavior?
Future of AI	How does he future of AI look like?
Attitudes towards AI	Likert-Scale: AI is the biggest disruptor in today's business world.
	Likert-Scale: An AI recommends firing a significant part of the workforce, would you?
	Do you think a future where AI makes major decisions without human oversight is plausible?
	Should humans have a discretionary override?

Table 6: Interview Questions - AI Experts

Appendix C: Questionnaire – Consumer Sentiment

Questions	**Answers**
How knowledgeable are you about Artificial Intelligence?	Likert-Scale (1 – not knowledgeable; 5 – very knowledgeable)
How knowledgeable are you about Machine Learning?	Likert-Scale (1 – not knowledgeable; 5 – very knowledgeable)
How do you feel about the future of AI?	Ranking: Hopeful; Excited; Anxious; Confident; Worried; Confused; Afraid
Description Scenario 1	You have worn glasses since childhood and decided to get laser surgery for $3.000 at a trusted clinic. Two weeks before surgery, you have a medical briefing with your surgeon. He explains the procedure and confirms that there are **no risks** associated with the surgery. Thus, you proceed with the surgery. It is successful, and you will never have to wear glasses again.
Would you perform the surgery?	Yes / No
Additional input Scenario 1	Instead of the surgeon, an AI performs the surgery. The briefing, risks, and outcome remain the same.
Would you pay the same amount?	Yes / No
If prev. question = No How much would you be willing to pay?	Multiple Choice: $500; $1,000; $1,500; $2,000; $2,500
Description Scenario 2	You are investing a portion of your net worth (~20%) through a wealth advisor who actively trades stocks in your portfolio. He charges a management fee of 2% and keeps 20% of your winnings. You have no say in which stocks are traded as long as your advisor abides

	by the law. Over the past decade, he has always delivered net of fee returns in excess of 3% compared to your benchmark, the S&P 500. Recently, your advisor was replaced by a machine learning algorithm for all buy and sell decisions. Future returns remain the same.
Would you be willing to pay the same fees?	Yes / No
Pension funds allocate capital to Private Equity (PE) managers. Your pension fund invests in a PE fund that extensively uses AI. How do you view this?	Likert-Scale (1 – strongly do not support; 5 – strongly support)
An AI recommends firing a significant part of the workforce to increase profitability. Would you?	Likert-Scale (1 – very unlikely; 5 – very likely)
Do you think a future where AI makes major decisions without human oversight is plausible?	Likert-Scale (1 – very implausible; 5 – very plausible)
Should humans have a discretionary override for AI decisions?	Yes / No

Table 7: Questionnaire - Consumer Sentiment

Appendix D: Additional Statistics

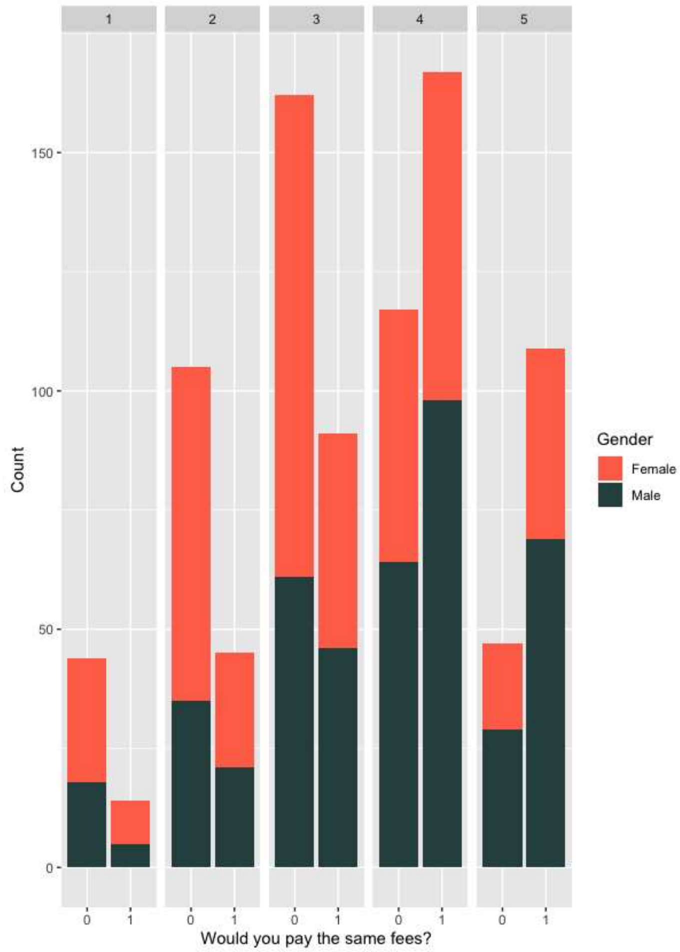

Figure 14: WTP Same Fees by AI Knowledge and Gender

	Q7/Q1	1	2	3	4	5
Expected Freq.	*No*	31	79	133	150	82
	Yes	27	71	120	134	74
Actual Freq.	*No*	44	105	162	117	47
	Yes	14	45	91	167	109

Table 8: Expected and Actual Freq. WPT Same Fees and AI Knowledge

Question	Correlation	Method
Q3 Excited	0.295***	Chi-square; Cohen w
Q3 Confident	0.316***	Chi-square; Cohen w
Q3 Hopeful	0.314***	Chi-square; Cohen w
Q3 Confused	0.268***	Chi-square; Cohen w
Q3 Worried	0.249***	Chi-square; Cohen w
Q3 Anxious	0.257***	Chi-square; Cohen w
Q3 Afraid	0.211**	Chi-square; Cohen w
Support PE AI (Q8)	0.851***	Chi-square; Cohen w
Major decision plausible (Q10)	0.556***	Chi-square; Cohen w
Discretionary Override (Q11)	0.024	Chi-square; Cohen w

*p<0.1; **p<0.05; ***p<0.01

Table 9: Various Correlations with AI Knowledge

Appendix E: Interview A

Occupation: AI PhD Resident

MM	**How many years of experience do you have with AI?**
A	• One year specifically in AI, longer with certain types of statistics
MM	**How can AI create value for companies?**
A	• Allows companies to make better decisions dependent on big data (both as decision support system & tracking bad decisions/ mistakes and the reasons behind them) • Automation - e.g., medical imaging • Boils down to all forms of data being processed by algorithms
MM	**What are major challenges for businesses trying to implement AI**
A	• Data privacy - e.g., hiring third party consultants to work with data or misbehaviors of data managers • Availability of good data → often missing data or incorrect data • Explainability → practitioners with lot of experience suddenly have machines/ algorithmic outputs telling them what to do without explanation
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
A	• Sounds good theoretically, but it is a question of expertise on all sorts of technical issues • Comes down to whether PE fund is better equipped than the portfolio company → it is not generalizable and needs to be evaluated on a case-by-case basis → often tech is thrown at industries without doing much – it is not a magic bullet solving everything
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
A	• AI coordinates behavior – has benefits and downsides → problems can propagate through the system = higher vulnerability to coordinated disaster, almost like centralization when companies use similar information, software, and algorithms • Humans can ignore irrelevant information, AI cannot → irrelevant things can have a big impact on the system
MM	**How does the future of AI look like?**
A	• Anything that is sort of repeatable and algorithmic is going to be taken over by AI • An intelligent agent might even be able to write a program smarter than itself • Period where specialization has been rewarded seems to be over → Soft skills and generalists with an overview probably more valuable in the future
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
A	5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**

A	2 – unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
A	• It is going on right now, and will continue to do so • Many business decisions are automated, however there may be a human overseer – usually for psychological comfort
MM	**Should humans have a discretionary override?**
A	• Yes, for political and democratic reasons (especially for areas such as autonomous weapons → people should be sovereign and will not give that up → comes down to trusting AI without explanation because it take into account more information or not

Table 10: Summary - Interview A

Appendix F: Interview B

Occupation: PE Principal

MM	**How long have you been working in PE?**
B	• Six years
MM	**How do you define value creation in PE?**

B	• Financial returns oriented:
	  ○ Buying a stream of cash flows and lever them
	  ○ Create value by reducing leverage with operating cash flows and operational improvements
	• ESG & Societal value creation

MM	**How do you measure it?**
B	• Compare returns → How much alpha do you create vs. beta (market) return • IRR • Fund to fund comparison → Is fund consistent in top quintile across same vintages? • Retroactive analysis → How are operations performing compared to initial investment scenario
MM	**How are you applying AI internally?**
B	• Not applying it currently – AI in PE in a very early stage
MM	**Since when have you been applying AI to your portfolio companies?**
B	• No mainstream application, but it is getting traction – especially in underwriting
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
B	• Integration of best practices from different people and different (cross-industry) transactions → building an institutional knowledge base • Some firms have large internal knowledge bases & create internal tech → can win more deals because they can pay more and still create excess value
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
B	4 – agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
B	2 – unlikely, but four or five in the future
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
B	• Yes, 100%
MM	**Should humans have a discretionary override?**
B	• Yes, AI should not get completely unchecked power without the ability to veto

Table 11: Summary - Interview B

Appendix G: Interview C

Occupation: Director, Head of AI & Data Science DACH

MM	**How many years of experience do you have with AI?**

C	• 40 years
MM	**How can AI create value for companies?**
C	• Streamlining processes o Natural language processing, ML automation • Data-driven and understandable decision making
MM	**What are major challenges for businesses trying to implement AI**
C	• Expectations too high • Ongoing management support → innovation can only happen in increments • Trust (Black box problem) – five ingredients for gaining trust: o Explainability, transparency, robustness, IT security, fairness
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
C	• Financial resources • Clever people how know how to optimize companies and identify use cases for AI • 95% if PE probably have much smaller AI capabilities than big tech
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
C	• Yes, of course e.g., algorithmic trading • Especially critical with autonomous weapons
MM	**How does the future of AI look like?**
C	• Trustworthiness major factor – EU AI Act is focused on it
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
C	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
C	• 1 – very unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
C	• No – there will always need to be someone in control, the EU AI Act demands it
MM	**Should humans have a discretionary override?**
C	• Yes

Table 12: Summary - Interview C

Appendix H: Interview D

Occupation: PE Principal

MM	**How long have you been working in PE?**
D	• 7 years
MM	**How do you define value creation in PE?**

D	• Everything that increases IRR
	    o Financial leverage → optimizing capital structure
	    o Operational improvements → more customers, marketing, incentives, rebranding, cost-cutting

MM	**How do you measure it?**
D	• IRR only measure → PE incentive structure based on it
MM	**How are you applying AI internally?**
D	• Currently not applying it → private market information not suitable for ML
MM	**Since when have you been applying AI to your portfolio companies?**
D	• No broad application
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
D	• Resources → hiring data scientists or programmers, inhouse AI development • Data sharing across portfolio companies → better ML models • Management alignment on AI use cases

MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
D	• Yes, market results seem more volatile since proliferation of ML
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
D	• 4 – agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
D	• 3 – neutral → currently AI is a decision support system, not a decision maker
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
D	• Eventually, given enough high-quality data is available
MM	**Should humans have a discretionary override?**
D	• Yes, but role of humans will diminish

Table 13: Summary - Interview D

Appendix I: Interview E

Occupation: Team Lead ML/Quantum Computing

MM	**How many years of experience do you have with AI?**
E	• 2.5 years
MM	**How can AI create value for companies?**
E	• Data-driven decision making → finding patterns • Product development (especially with quantum computing) e.g., new drugs → delete human error by directly looking at processes at molecule level
MM	**What are major challenges for businesses trying to implement AI**
E	• Data quality and availability • Current AI is limited to human knowledge • Exposed to manipulation if it is trained while deployed • Explainability → AI is a black box • No general ethical code to train AI → Ethics are not binary, AI is
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
E	• Data and knowledge transfer across industries to enhance algorithms • Scaling AI
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
E	• Yes, if decision/ recommendation is based on same info • AI usually incorporates programmer's biases → people using that algorithm will be exposed
MM	**How does the future of AI look like?**
E	• ML based on quantum computing → current computational power still too limited for complex models e.g., precise weather or economic forecasts, effects of climate change
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
E	• 4 – agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
E	• 3 – neutral → would want to understand why AI is recommending it
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
E	• Plausible, but probably not recommendable due to morality and ethics
MM	**Should humans have a discretionary override?**
E	• Yes, especially when decisions concern well-being of humans • Not just one, but a group of experts shining light on black box

Table 14: Summary - Interview E

Appendix J: Interview F

Occupation: PE Associate

MM	**How long have you been working in PE?**
F	• 2 years
MM	**How do you define value creation in PE?**
F	• Providing capital, oversight, and guidance
MM	**How do you measure it?**
F	• IRR • Business-specific KPIs → recurring revenue, churn rate
MM	**How are you applying AI internally?**
F	• Data analysis
MM	**What are your plans with AI in the future?**
F	• Data-driven portfolio management • Spotting trends for investment decisions
MM	**Since when have you been applying AI to your portfolio companies?**
F	• Quite recently, but statistics/ data analysis for a while
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
F	• PE inhouse data architects/ ML engineers • Alleviating financial constraints →Ai is expensive • Advantage biggest with organic use case • Cross-industry expertise
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
F	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
F	• 4 – likely, but AI needs to be well-trained and have objective reasons
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
F	• Yes, already happening in some industries
MM	**Should humans have a discretionary override?**
F	• Yes, if it involves danger to human life

Table 15: Summary - Interview F

Appendix K: Interview G

Occupation: Founder

MM	**How many years of experience do you have with AI?**
G	• One intense year
MM	**How can AI create value for companies?**
G	• Process efficiencies through automation → removing human driven cost centers • Almost all human oriented tasks can be supplemented by AI input • AI as platform technology similar to the mobile platform
MM	**What are major challenges for businesses trying to implement AI**
G	• Cultural → changing people's behavior to actually use AI daily • Training people on how to use AI efficiently → prompting will be very important • Trustworthiness & explainability → e.g., there is no fact checking for GPT output and humans need to be aware of potentially wrong output if actionable items are derived
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**

G	• Expertise & knowledge • Existing tools that can be leveraged • However, seems like the company with better AI knowledge seems to be better off regardless
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
G	• Yes, herding behavior might be increased in the short term • More differentiated offerings and less herding in the long term due to refined and differentiated models
MM	**How does the future of AI look like?**
G	• AI as a platform technology where different applications are built on (B2B and B2C) • Fundamental change in structure and behavior for white collar jobs → AI is going to be scary good in a few years • Large portions of jobs will get automated (e.g., financial sector: investment banking) • Every consumer will be forced to accept, understand, and adopt AI
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
G	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
G	• 3 – neutral
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
G	• Yes, but we are going to try to not allow that for as long as possible • Humans in control is going to be a center point of AI protocols
MM	**Should humans have a discretionary override?**
G	• Yes

Table 16: Summary - Interview G

Appendix L: Interview H

Occupation: PE Founder & Managing Partner

MM	**How long have you been working in PE?**
H	• 10 years
MM	**How do you define value creation in PE?**
H	• Difference between value of equity at entry and exit
MM	**How do you measure it?**
H	• IRR
MM	**How are you applying AI internally?**
H	• Currently not using it
MM	**What are your plans with AI in the future?**
H	• Internally not a priority, but fund is solely focused on applying AI to portfolio companies
MM	**Since when have you been applying AI to your portfolio companies?**
H	• Just started using it, but long experience as their VC was the first fund to solely focus on AI globally • No internal developers
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
H	• Identify use case and provide knowledge of available technology • Network, especially if specific AI tech is not available for broader market • Relationship management with third-party experts • Oversight and strategic guidance • Increase AI acceptance/ willingness to implement AI due to concentrated ownership
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
H	• Yes
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
H	• 4 – agree

MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
H	• 1 – very unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
H	• Yes, I can imagine it, but I think it is terrible
MM	**Should humans have a discretionary override?**
H	• Yes, 100%

Table 17: Summary - Interview H

Appendix M: Interview I

Occupation: CEO

MM	**How many years of experience do you have with AI?**
I	• 7 years
MM	**How can AI create value for companies?**
I	• In all areas except for image generation
MM	**What are major challenges for businesses trying to implement AI**
I	• Mindset for required cultural change • Fear of employees → job losses due to automation
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
I	• Expertise • Network • Cross-industry experience
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
I	• Yes, risks exists, but might not be higher than human risks, it just shifts elsewhere
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
I	• 2 – disagree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
I	• 1 – very unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
I	• Yes, 100%
MM	**Should humans have a discretionary override?**
I	• Yes, from today's point of view, but it depends on the decision • However, if you do not trust the decision, you could basically not use AI at all

Table 18: Summary - Interview I

Appendix N: Interview J

Occupation: Director Portfolio Operations

MM	**How long have you been working in PE?**
J	• 2.5 years
MM	**How do you define value creation in PE?**
J	• Any activity that you can either incentivize, accelerate, or apply to the assets that you are acquiring such that the exit value is higher than the entry value
MM	**How do you measure it?**
J	• EBITDA multiples
MM	**How are you applying AI internally?**
J	• Accelerating analytics

	• Enhancing the build process
MM	**What are your plans with AI in the future?**
J	• Deal sourcing • Due diligence processes, although it is a very subjective topic and will not be entirely done by AI
MM	**Since when have you been applying AI to your portfolio companies?**
J	• Our PE was founded to apply AI → from the beginning (2.5 years)
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
J	• PE inhouse AI development → external specialists (consultants, programmers) are expensive • Cross-industry expertise • Knowledge transfer to make companies self-sustaining in the future • Finding (internal and external) and hiring talents • Aligning and prioritizing AI strategy within business strategy (instead of treating it as a sideline project) • Top-down management alignment • Helping with (cultural) change management
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
J	• Not necessarily in PE as funds are already aiming for the same targets
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
J	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
J	• 3 – neutral, I do not think AI will fire people but repurpose roles
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
J	• Benefits of AI making decisions are far exposed when the volume of decisions is high and when making quick optimal decisions is hard for a human being • If major decision means a few decisions, than I do not see many benefits
MM	**Should humans have a discretionary override?**
J	• It is normally expected and builds trust, for that reason: Yes

Table 19: Summary - Interview J

Appendix O: Interview K

Occupation: Managing Director EMEA; Professor

MM	**How many years of experience do you have with AI?**
K	• 12 years
MM	**How can AI create value for companies?**
K	• Automating everything somewhat repetitive → this is also where humans make most mistakes
MM	**What are major challenges for businesses trying to implement AI**
K	• Data quality and currently availability although companies should learn how to use small data for algorithms • Cyber security risks
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
K	• Overall, PE will be an accelerator for AI initiatives • Drive ownership for AI • Expertise • Cross-industry knowledge transfer • Network of advisors and experts
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
K	• Yes, systemic risks exist through interaction of multiple intelligent agents
MM	**How does the future of AI look like?**
K	• AI will be ubiquitous such as energy/ electricity

	• Quantum computing necessary to enable the bright AI future
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
K	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
K	• 3 – neutral
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
K	• No, although there might be a multipurpose AI to answer almost every question (probably really expensive for the next 15-20 years)
MM	**Should humans have a discretionary override?**
K	• Yes, if humans are at risk or really big topics – otherwise no

Table 20: Summary - Interview K

Appendix P: Interview L

Occupation: Data Scientist

MM	**How many years of experience do you have with AI?**
L	• 5 years
MM	**How can AI create value for companies?**
L	• Filtering and analyzing data • Classifications • Decision support system (providing recommendations)
MM	**What are major challenges for businesses trying to implement AI**
L	• Trusting AI's recommendations • Data quality • Ethics
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
L	• Expertise • Providing resources
MM	**How does the future of AI look like?**
L	• More automation • Larger adoption → example ChatGPT • Simply enhanced technology
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
L	• 2 – disagree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
L	• 2 – unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
L	• Yes, although hard to define major decisions
MM	**Should humans have a discretionary override?**
L	• Yes, for every decision because humans are better in explaining decisions to other humans

Table 21: Summary - Interview L

Appendix Q: Interview M

Occupation: Managing Partner

MM	**How long have you been working in PE?**
M	• 18 years

MM	**How do you define value creation in PE?**
M	• Positive return after exiting a business ○ bottom-line improvements through product expansions or new market entries
MM	**How do you measure it?**
M	• MOIC
MM	**How are you applying AI internally?**
M	• Currently not applying it • AI mostly a buzzword in PE, because buying companies is a people business
MM	**What are your plans with AI in the future?**
M	• No concrete plans → mostly as marketing tool for fundraising
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
M	• Ownership structure can help with management alignment ○ Ensuring management commitment even if they cannot envision how it will work • Aligning AI strategy with business strategy
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
M	• 5 – strongly agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
M	• 5 – very likely; if it is trained enough to make a decision, it should be followed
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
M	• Very plausible and probably better for society in general
MM	**Should humans have a discretionary override?**
M	• No

Table 22: Summary - Interview M

Appendix R: Interview N

Occupation: EMEA Trustworthy AI Lead; Vice President AI Research

MM	**How many years of experience do you have with AI?**
N	• 10 years
MM	**How can AI create value for companies?**

N	• Efficiencies through automation → including cognition related tasks that have never been automated before
	• Huge potential in innovation power → that is why it is so disruptive
	  ○ Completely new products and services (e.g., healthcare, financial services: financial inclusion)
	  ○ New source of inspiration to explore what is even possible → new form of computing that inspires a new way of thinking
	• Forcing companies to actually approach a healthy transformation journey, which is necessary for AI

MM	**What are major challenges for businesses trying to implement AI**
N	• Required organizational structure or functions not in place or aligned → delivery and operating model not agile or multidisciplinary enough • Building fair and trustworthy AI → many companies not used to think about ethical, social, or regulatory implications ○ Explainability a major dimension for trustworthiness • Engineering discipline to make it productive at larger scale • Cultural → no business buy in because AI is seen as IT topic → AI strategy needs to be part of enterprise strategy
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**

N	• Experience to avoid a lot of pitfalls
	• Management alignment
	  ○ having the business buy-in from the very beginning
	  ○ higher adoption rate

	◦ making sure AI is used with more purpose and for the right value • ability to operationalize and scale AI might be improved as well
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
N	• It but depends a lot on the design and development processes → no large risks because there is a lot of human interaction in current processes • Transparency on which data a model is trained also important → this might be a downside of third-party developers
MM	**How does the future of AI look like?**
N	• Transformation has just started → people are just starting to realize the impact of AI • Trustworthiness will be a major aspect, because of regulation and it is becoming more important due to scale of AI • Democratization of AI → more people with access to build their own AI
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
N	• 4 – agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
N	• 1 – strongly disagree
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
N	• It is, but we are working towards preventing it – at least in high-risk areas • High-risk area = potential to harm people (psychological, physical, and economical)
MM	**Should humans have a discretionary override?**
N	• Yes, especially in risky areas • In some areas we can rely on it as long as we monitor it

Table 23: Summary - Interview N

Appendix S: Interview O

Occupation: BI Consultant

MM	**How many years of experience do you have with AI?**
O	• 2 years
MM	**How can AI create value for companies?**
O	• Assisting in automation of somewhat repetitive tasks • Helping in decision-making within complex non-linear business cases • Pointing to previously undiscovered factors affecting a response variable • Managing resources when supervised
MM	**What are major challenges for businesses trying to implement AI**
O	• Required infrastructure to (re-)train, deploy, and monitor hundreds of models in various stages at scale in an automated and fully documented way • Broad spectrum of know-how • Explainability, especially in relation to fairness and introduced biases • Financial resources to afford running models and ML engineers
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
O	• Does not fundamentally change the ways of how AI can create value
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
O	• Not an inherent flaw • Less likely due to large number of predictors and tests to ensure ML ability to predict the response variable
MM	**How does the future of AI look like?**
O	• Bright, we have not even begun to scratch the surface • AI will not be able to solve all our problems
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**

O	• 4 – agree
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
O	• 1 – very unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
O	• Plausible, but at least currently inadvisable
MM	**Should humans have a discretionary override?**
O	• Always

Table 24: Summary - Interview O

Appendix T: Interview P

Occupation: Senior Associate

MM	**How long have you been working in PE?**
P	• 5 years
MM	**How do you define value creation in PE?**
P	• Risk mitigation, including accidents, fatalities, etc. • Bottom line improvements • Priority is to realize value for investor
MM	**How do you measure it?**
P	• IRR • Safety metrics such as lost time incident rates
MM	**How are you applying AI internally?**
P	• Not currently applying it
MM	**What are your plans with AI in the future?**
P	• Using AI from an asset management, origination, and transaction perspective
MM	**Since when have you been applying AI to your portfolio companies?**
P	• 2021, we started earlier but 2021 was when it became something actually useful and not just a buzzword • Only in targeted investments
MM	**What advantages do your portfolio companies have when applying AI compared to their non-backed peers?**
P	• Cross-industry knowledge transfer • Transfer AI solutions across multiple portfolio companies (e.g., AI solutions for airports) • Cost advantages when it comes to procurement processes • Depends on the maturity of the company, probably negligible and potentially destructive for digital native companies
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
P	• Potentially, but not necessarily in PE, because there is much more to PE than looking at data
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
P	• 3 – neutral
MM	**Likert-Scale: An AI recommends firing a significant part of the workforce, would you (1 – very unlikely; 5 – very likely)?**
P	• 2 – unlikely
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
P	• No, there will always be human intervention in strategic matters (ranging from nuclear launch to investments in companies)
MM	**Should humans have a discretionary override?**
P	• Yes, humans should always have oversight → it is a support system not a decision-maker

Table 25: Summary - Interview P

Appendix U: Interview Q

Occupation: Generative AI

MM	**How can AI create value for companies?**
Q	• Increase efficiency • Improve decision-making • Enhance customer experience • Cost savings • Product innovation
MM	**What are major challenges for businesses trying to implement AI**
Q	• Data quality and availability • Talent shortage • Integration with existing systems • Lack of understanding • Cultural resistance to change • Ethical and legal considerations (e.g., explainability and accountability) • High development and implementation costs
MM	**How could someone like a PE fund create value by enabling AI in its portfolio companies?**
Q	• Identify use cases • Provide resource • Facilitate partnerships • Drive operational improvements • Strategic guidance
MM	**Is it possible that AI leads to phenomena such as herding behavior or increased systemic risks in general?**
Q	• Yes, due to biased training data, lack of diversity in training data, lack of transparency or feedback loops
MM	**How does the future of AI look like?**
Q	• AI is rapidly evolving; it will be better at everything it can do now and more • Ethical considerations will become more important
MM	**Likert-Scale: AI is the biggest disruptor in today's business world (1 – strongly disagree; 5 – strongly agree).**
Q	• 5 – strongly agree
MM	**Do you think a future where AI makes major decisions without human oversight is plausible?**
Q	• Yes, but significant ethical and technical challenges exists → Explainability and biases major problems
MM	**Should humans have a discretionary override?**
Q	• Advisable in most cases → can be a useful tool for ensuring AI systems are used in a responsible and ethical way

Table 26: Summary - Interview Q