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Towards Understanding the Use of Artificial Intelligence in Hybrid Retail Platforms: Insights from 66 Use Cases

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Short Paper

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Abstract

Research predicted the use of artificial intelligence (AI) in electronic commerce long before electronic commerce and AI became ubiquitous in everyday life. AI was envisioned to reduce the effort of participating in electronic commerce (i.e., transaction costs), so that buyers could benefit from the ever-expanding exchange opportunities in a digitalized world. The existing literature, however, has focused on developing performant AI technologies, and given their business function less attention. We therefore know much about the potential and little about the actual AI use in electronic commerce. This qualitative research-in-progress addresses this issue by delineating 66 AI use cases at Germany's leading hybrid retail platform (OTTO) along relational, processual, and functional context dimensions. Preliminary results indicate that AI is used primarily to reduce search & information costs in consumer-oriented and policing & enforcement costs in business-oriented segments. Moreover, AI is used to manage dynamics between consumer- and business-oriented segments in hybrid retail platforms.

Keywords: Artificial Intelligence, Hybrid Retail Platforms, AI Use Cases, Case Study

Introduction

The Internet will account for over 21 percent of global retail sales by 2029 (Statista, 2025). Growth in electronic commerce is driven by online marketplaces (Grand View Research, 2025), where consumers can choose from a variety of products offered by different sellers (Tian et al., 2018). Following Amazon's lead in 2000, many online retailers adopted a hybrid business model and opened their platforms to third-party sellers (Hänninen et al., 2017; Ryan et al., 2012; Trabucchi & Buganza, 2022). Recent examples include Walmart, BestBuy, and Target in North America. ePrice, OTTO, and Kaufland in Europe.

Information systems research on electronic commerce predicted this global phenomenon decades before (Alt, 2017, 2020; Alt & Klein, 2011; Malone et al., 1987; Wigand, 1997). In their seminal paper, Malone et al. (1987) posit that advances in information technology reduce transaction costs (Coase, 1937; Williamson, 1971). Which they argued forces businesses to organize as *unbiased* electronic markets that broker third-party offerings, since customers ultimately seek greater choice. However, unbiased markets might overwhelm customers with more alternatives than they can potentially consider (Malone et al., 1987). Therefore, unbiased markets will therefore become *personalized* and provide "decision aids" (Malone et al., 1987) that help individual buyers identify the best option to profit from the ever-increasing exchange opportunities in a digitalized world (Wigand, 1997). To this end, Malone et al. (1987) envisioned the use of artificial intelligence technologies in electronic commerce.

In recent years, the research interest in the intersection of AI and electronic commerce increased considerably (Bawack et al., 2022). Broadly speaking, the literature tends towards the technological end of

the sociotechnical axis (Sarker et al., 2019). That means existing research has largely focused on developing high-performant AI technologies and paid less attention to their real-world use (Bawack et al., 2022). Hence, we know a lot about the *potential* and little about the *actual* use of AI in electronic commerce. This may be partly because access to electronic commerce businesses from "within" is difficult to obtain (de Reuver et al., 2018). Regardless, our limited understanding of the actual AI use in electronic commerce is problematic. Because we are unlikely to realize the positive vision of early electronic commerce research (Malone et al., 1987) if we focus solely on building increasingly performant AI technologies – without understanding the contexts in which they are used to create value (Ågerfalk, 2020; Bawack et al., 2022).

This research-in-progress addresses this issue by investigating the use of AI in electronic commerce in a real-world setting. I pose the following research question: *In which ways is AI currently used to create value in hybrid retail platform businesses?* To answer the research question, I am conducting an embedded case study (Yin, 1994) of 66 AI use cases at Germany's leading electronic commerce company "OTTO". Building on transaction cost theory (e.g., Coase, 1937; Dahlman, 1980; Williamson, 1971, 2010) and a taxonomy of high-level AI capabilities (Yildirim et al., 2023), I delineate these use cases along *relational*, *processual,* and *functional* context dimensions (Ågerfalk, 2020) to understand how AI creates value in OTTO's hybrid retail platform business.

Initial findings indicate that AI creates is used across OTTO's hybrid retail platform business to create value by reducing transaction costs. However, the types of transaction costs reduced differ between business segments, and these reductions require different (combinations of) high-level AI capabilities (Yildirim et al., 2023). The preliminary analysis further suggests that AI is used to manage interactions between business-to-consumer and business-to-business segments.

My overall goal with this research project is to help (re)direct the research interest towards the *actual use* and *business value* of AI in electronic commerce - where it resided long before the phenomena became ubiquitous and observable.

Conceptual Background

It is widely acknowledged in information systems research that AI, like any technology, does not create value by itself, but through the business processes it enables (Ågerfalk, 2020; Wigand, 1997). Hybrid retail platforms business is essentially about facilitating exchange processes between different parties that unfold over time (Tian et al., 2018). From this characterization, three dimensions can be derived to connect an AI system to the hybrid retail platform context (Ågerfalk, 2020; Bawack et al., 2022) in which it is used: a *relational* dimension (between which parties is the AI system used?), a *processual* dimension (in which phase of the exchange process is the AI system used?), and a *functional* dimension (for what purpose is the AI system used?). One possible strategy to study the use of AI in a hybrid retail platform business is to first capture information along these contextual dimensions at the level of individual use cases and then integrate it across all cases. Capturing the *relational*, *processual*, and *functional* information on AI use in hybrid retail platforms requires complementary perspectives (Burton-Jones et al., 2015). In the following, I outline the perspectives that guide this research-in-progress and explain how they are operationalized.

Capturing Relational Information on AI Use in Hybrid Retail Platforms

To capture relational information on AI use, I draw on Zhao & Luo's (2022) capital flow model, as it provides a sufficiently abstract view of the relevant parties in hybrid retail platform business. In their model, a hybrid retail platform is characterized as a business in which the operating enterprise runs both a platform business and a self-operated business. In the platform business, the operating enterprise brokers transactions between consumers and third-party sellers but does not directly participate in the exchange (Zhao & Luo, 2022). In the self-operated business, the operating enterprise acquires products from suppliers and sells them to consumers (Zhao & Luo, 2022). From this conceptualization, relational information on AI use can be captured by identifying whether an AI system is used between *Operating Enterprise*, *Platform Business*, *Self-Operated Business*, *Consumers*, *Third-Party Sellers*, or *Suppliers*.

Capturing Processual Information on AI Use in Hybrid Retail Platforms

To capture processual information on the use of AI, I draw on transaction cost theory. This is because transaction cost theory is well established for studying the intersection of information technologies and electronic commerce (Alt, 2017, 2020; Glassberg & Merhout, 2007). As mentioned in the introduction, it is frequently used to conceptualize the value contribution of information technology by operationalizing it through the reduction of transaction costs (Alt, 2017), thereby helping to explain the genesis and evolution of electronic commerce as such (Malone et al., 1987). More recently, scholars suggested to apply transaction cost theory to AI specifically (Andersen, 2024; Cuypers et al., 2021; Nagle et al., 2024). For it was argued that machine learning (ML)-based AI can reduce transaction costs in novel ways (Andersen, 2024). After all, ML-based AI systems are programmed to learn from data using statistics (Jordan & Mitchell, 2015; Samuel, 1959). Which promises online hybrid retail businesses an easier way to "model order" (Heylighen, 1999) and generate information on the many buyers, sellers, and products on their platforms.

Transaction Cost Type	Arises Because of …
Search & Information	Imperfect information regarding existence and location of trading opportunities, quality or other characteristics of items available for trade
Bargaining & Decision	Imperfect information regarding (mutual) desire of economic agents to participate in trading at specific prices and conditions
Policing & Enforcement	Imperfect information regarding whether the parties involved in the agreement will fulfill their contractual obligations

Table 1. Taxonomy of Transaction Costs (Dahlman, 1980).

Hence, AI systems can be differentiated by the type of imperfect information they address in the three stages of transaction processes outlined by Dahlman (1980). From this conceptualization, processual information on AI use can be captured by identifying whether an AI system addresses imperfect information in the *Search & Information*, *Bargaining & Decision*, or *Policing & Enforcement* stage.

AI Capability	Short Definition	Example
Estimate	Infer a value related to the current situation	Estimate driving time
Forecast	Infer a value that will be true or some attribute or impact of a future situation that may or may not happen	Forecast best time to buy stock
Compare	Compare a collection of like items based on a metric	Compare posts by likely engagement
Detect	Notice if a specific kind of a thing is in a data set or if it shows up in a sensor stream	Detect human voice in audio
Identify	Notice if a specific item or class of items shows up in a set of like items	Identify cancer type in medical image
Discover	Analyze a dataset and notice a pattern that allows clustering of similar things or identification of outlying entities	Discover unusual bank transactions
Generate	Generate something new based on knowledge of similar things	Generate synthetic medical records
Act	Execute a strategy to achieve a specific goal and continue to update the strategy based on advance towards the goal	Act: Fly drone to location

Table 2. Taxonomy of High-Level AI Capabilities (Yildirim et al., 2023).

Capturing Functional Information on AI Use in Hybrid Retail Platforms

To capture functional information on the use of AI, I draw on the taxonomy of high-level AI capabilities proposed by (Yildirim et al., 2023). As highlighted by prior research, it is particularly important in studies at the intersection of AI and electronic commerce to specify what is meant by AI in order to avoid ambiguity (Bawack et al., 2022). The taxonomy conceptualizes ML-based AI by the types of problems such systems

are typically used to solve (Table 2). This functional perspective backgrounds the algorithmic mechanics and foregrounds the purpose(s) that AI systems serve in a business context, which aligns closely with the aim of this study. Yildirim et al. (2023) further suggest a unified grammar to express AI use cases as statements of *[Action] + (Inference) + {Data/Entity/Metric}*. From this conceptualization, functional information can be generated by classifying an AI use case according to *Estimate*, *Forecast*, *Compare*, *Detect*, *Identify*, *Discover*, *Generate*, or *Act*. An additional benefit of using this grammar is that it facilitates the integration of contextual information on individual AI use cases in later research stages.

Propositions Regarding the Use of AI in Hybrid Retail Platforms

To the best of my knowledge, the use of AI in hybrid retail platforms has not yet been addressed in the literature. However, existing studies provide observations on how information technologies in general, and AI in particular (may), affect transaction costs. These observations can be connected to the *relational*, *processual*, and *functional* context dimensions conceptualized above, and thereby guide the derivation of propositions for this study. First, with respect to the *processual* and *functional* dimensions, Andersen (2024) argues that "AI primarily impacts pre-contractual phases". Second, with respect to the *processual* and *relational* dimensions, Glassberg & Merhout (2007) suggest that different types of transaction costs are more salient depending on the business context: search and price-related issues in consumer-oriented segments, and relational concerns in business-oriented segments.

Based on these observations, two propositions about the use of AI in hybrid retail platforms can be derived to guide empirical investigations:

Proposition 1: In business-to-consumer oriented segments, hybrid retail platform businesses use AI primarily to reduce *Search & Information* costs.

Proposition 2: In business-to-business oriented segments, hybrid retail platform businesses use AI primarily to reduce *Policing & Enforcement* costs.

Research Design

I have chosen a qualitative case study approach for this research. This is because case studies are the ideal method (Yin, 1994) for studying contemporary phenomena (the use of AI) in their real-world context (hybrid retail platform business). Following Yin (1994), I designed the case study around theory-informed propositions (see above). My prior theoretical understanding suggested that the use of AI might vary between consumer- and business-oriented segments in hybrid retail platform business. I therefore decided to conduct an embedded single case study allows for an in-depth understanding while capturing contextual variation by breaking the analysis into multiple sub-units (Yin, 1994).

My research strategy is hence to focus on one hybrid retail platform and understand the use of AI by analyzing the AI use cases employed by the respective organization. My research strategy benefits from collecting data within the organization and working closely with practitioners (Bawack et al., 2022). Access to platform businesses is difficult to obtain and data from "within" those organizations therefore rare (de Reuver et al., 2018). Any case study from "within" a hybrid retail platform could hence provide valuable insights. However, there are at least two criteria to consider for case selection. First, scholars have urged to investigate the use of AI in electronic commerce other than the major US and Chinese examples that are typically studied (Bawack et al., 2022). Second, the case organization needs to have sufficient AI use cases in place that can be studied in an embedded design. While the number of AI use cases is difficult to determine in advance, AI-related company communication can provide an indication (e.g., executive interviews, press releases, newspaper articles). Based on these criteria, I selected a European organization to study the use of AI in hybrid retail platforms: Germany's leading electronic commerce company OTTO.

OTTO is a family-owned retail company based in Hamburg, Germany. Werner Otto founded the company in 1949 as a catalogue-based mail order business. Since then, OTTO's business model has evolved and been digitally transformed. Today, OTTO operates a hybrid retail platform business. On "Otto.de", more than 12.2 million active users can choose from over 18 million products offered by OTTO and 6,200 third-party-sellers (Otto, 2024). This makes OTTO the largest player in the German electronic commerce market after Amazon, with a gross revenue of seven billion euros (Otto, 2024).

OTTO has been using AI technologies for more than a decade. AI has played a crucial role in OTTO's business transformation. As the CEO noted: *"Initially, only about 15 percent of our employees were tech oriented. […] We now have […] 400 colleagues in business intelligence, […] over 65 AI use cases up and running."* (OMR, 2024). OTTO documents AI use cases in a central repository ("AI catalogue"). This AI catalogue provides the empirical basis for this research. OTTO's AI catalogue documents use cases where the company has allocated human resources (i.e., product teams) to develop, deploy, and maintain AI systems. The allocation of dedicated personnel indicates that these AI use cases are particularly relevant to OTTO's business. For each AI use case, the AI catalogue records metadata (e.g. ID, title, status) and information from a business (e.g., use case description, start date, stakeholders, business impact, value contribution) and technology perspective (e.g., description of the AI system, AI methods used, data sources, risks, learn frequency, link(s) to code/documentation). OTTO uses the AI catalogue to manage its AI activities. The AI catalogue therefore provides the best available approximation of the use of AI in OTTO's hybrid retail business. My study is based on a version of the AI catalogue with a total of 66 AI use cases.

[1] Research Preparation. I began by modelling OTTO's hybrid retail platform business according to the transaction parties identified by Zhao & Luo (2022). In addition to the parties they listed, I found *Competitors, Intermediaries,* and *Employees* to be relevant for capturing relational information on AI use in OTTO's business and therefore added them. I evaluated and refined the model with OTTO's Chief AI Officer and a Senior AI Management Expert. **[2] Data Collection.** Next, I built the case study corpus by extracting all 66 entries from OTTO's AI catalogue into a consolidated spreadsheet. Where necessary, I supplemented this data with information from technical documentation and business presentations retrieved from sources such as the company intranet, JIRA, Confluence, and online whiteboards. **[3] Data Preparation.** The quality of documentation in OTTO's AI catalogue varied considerably. I therefore represented all 66 AI use cases in a standardized grammar following Yildirim et al. (2023). For example, I represented the description "*Using real-time analysis of user behavior, the technology identifies fraudulent behavior to prevent fraud and reduce bad debts*" as *[Identify] + (Fraud)+ in {User Behavior}*. The coding of all 66 AI use cases was validated by an AI project manager responsible for maintaining OTTO's AI catalogue. **[4] Data Analysis.** I first used my model of OTTO's hybrid retail platform business to determine relational information. That is, the transaction parties between which each AI use case operates (e.g., *Platform Business* and *Consumers*). Next, I assessed the presence or absence of each of the eight high-level AI capabilities (Yildirim et al., 2023) to capture functional information. I then used the descriptions of the business impact to identify which transaction cost type each AI use case primarily reduces (*Search & Information*, *Bargaining & Decision*, or *Policing & Enforcement*), thereby capturing processual information. Finally, I combined the output of these assessments to form preliminary AI use case clusters (e.g., customer fraud prevention) and mapped them onto my model of OTTO's hybrid retail platform business. Again, all classifications were validated by an AI project manager. The preliminary results provide an initial view on how AI is used across different relational, processual, and functional contexts in OTTO's hybrid retail platform business.

I evaluated the preliminary results of my analysis with OTTO practitioners (including the Chief AI Officer, a Senior AI Management Expert, and an AI Project Manager). I am going to present two key artifacts of my ongoing research in the subsequent section of this paper.

Preliminary Case Study Results

My ongoing case study of Germany's leading retail company OTTO has yielded initial insights regarding the use of AI in hybrid retail platform business. Figure 1 provides an integrated overview of these insights. The diagram combines relational and processual dimensions: the nodes represent transaction parties (relational context), while the connecting lines indicate the transaction relations between them. The thickness of each line corresponds to the number of AI use cases identified in that relation, thus serving as a proxy for the extent of AI exposure. The color of each line indicates the processual context, i.e., which type of transaction cost is primarily reduced by AI in that relation (search & information, bargaining & decision, or policing & enforcement). Finally, the numbers in the boxes serve as reference points to Table 3, which provides the detailed classification of use cases along all three context dimensions (relational, processual, functional).

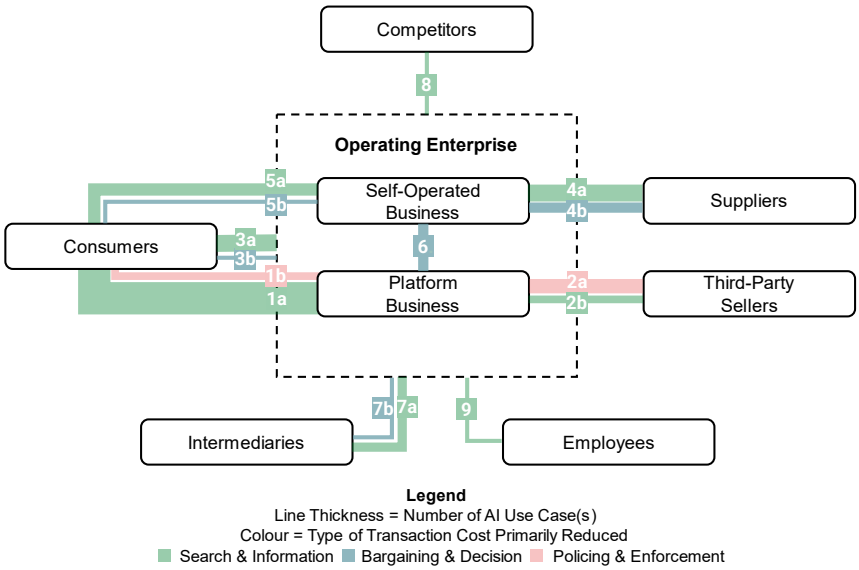

Figure 1. AI Use in OTTO's Hybrid Retail Platform Business. Based on Zhao & Luo (2022).

Page limitations do not allow me to comment on all the data displayed in Figure 1 and Table 3. Instead, I will focus on the initial findings that are particularly relevant to the propositions guiding my research. Hence, I will focus on the use of AI in both the consumer- and business-oriented segments of OTTO's hybrid business (i.e., *Platform Business* and *Consumers* [#1a, 1b]; *Platform Business* and *Third-Party Sellers* [#2a, 2b]), as well as the "internal" relationship between *Self-Operated Business* and *Platform Business* [#6]. I will provide examples of OTTO's AI use cases as far as confidentiality agreements permit.

[#1a, 1b] AI Use Between Platform and Consumers. This consumer-oriented segment has the most AI use cases in my sample. My preliminary analysis suggests that AI predominantly reduces *Search & Information* costs between *Platform Business* and *Consumers* [#1a]. This is consistent with theory-informed expectations (Proposition 1). I have identified four AI use case clusters that reduce search and information costs between consumers and platform (i.e., helping consumers find products, discover products, engaging them on own digital channels, and identifying consumer needs). For example, OTTO uses AI to display suggestions for keyword searches, recommend similar or complementary products, or adapt navigation elements on the platform. I found that these and other AI use cases tend to combine several of the eight high-level AI capabilities. With the capability to "compare" different objects based on metrics being particularly present. My analysis further indicates that AI reduces *Policing & Enforcement* costs between *Platform Business* and *Consumers* [#1b]. I have identified two clusters of AI use cases: preventing customer fraud, and handling customer inquiries. For example, OTTO uses AI to prevent fraudulent orders and to ensure legally compliant responses to customer inquiries. For these and other use cases, AI's capability to assess current states ("estimate") appears to be particularly important.

[#2a, 2b] AI Use Between Platform and Third-Party Sellers. This business-oriented segment has the second highest number of AI use cases in my sample. My analysis suggests that AI is primarily used to reduce *Policing & Enforcement* costs between *Platform Business* and *Third-Party Sellers* [#2a], which is consistent with the theory-informed expectations outlined in Proposition 2. I have identified two preliminary clusters of AI use cases in this segment: ensuring third-party compliance, and preventing third-party errors. OTTO, for example, uses AI to detect potential instances of review fraud or incorrect product information provided by marketplace partners. For these use cases, AI's capabilities to notice the presence of specific objects ("identify") or object types ("detect") seem particularly prominent. My research also suggests that AI is being used to reduce *Search & Information* costs between *Platform Business* and *Third-Party Sellers* [#2b]. I have identified two preliminary AI use case clusters in this context: identifying needs of third-party sellers and handling their inquiries. OTTO, for instance, uses an AI-powered chatbot to manage first-level marketplace partner support. For these and other use cases in this segment, the AI capabilities "generate" and "identify" seem particularly relevant.

[#6] AI Use Between Platform and Self-Operated Business. This segment also has a considerable number of AI use cases in my sample. My analysis suggests that the *Self-Operated Business* uses AI primarily to reduce *Bargaining & Decision* costs. So far, I have identified two AI use case clusters: defining the product assortment of the self-operated business and ensuring competitive pricing. For example, OTTO uses AI to decide which products the self-operated business should offer, and which should be complemented by third-party sellers. For these and other use cases, AI's capabilities to "forecast" future states, "generate", and "act" on decision rules appear to be particularly important. The use of AI between the *Platform Business* and *Self-Operated Business* in hybrid retail platforms is particularly interesting, as assortment and pricing decisions link consumer- and business-oriented segments. I have not anticipated this interrelation at the outset of my research. It points to a dynamic between business- and consumer-oriented segments in hybrid retail platform business that may warrant further exploration.

#	Preliminary AI Use Case Clusters	Reduction of	Capability Frequency							
			E	**F**	**C**	**D_e**	**I**	**D_i**	**G**	**A**
1	Platform Business ⇔ Consumers									
1a	• Find Relevant Products • Discover Relevant Products • Engage Consumers on Own Digital Channels • Identify Needs of Existing Consumer(s)	S&I Costs	◑	◔	●	◔	◑	◑	◑	○
1b	• Prevent Customer Fraud • Handle Customer Inquiries	P&E Costs	●	○	○	◑	◑	◑	○	○
2	Platform Business ⇔ Third-Party Sellers									
2a	• Ensure Compliance of Third-Party Seller(s) • Prevent Errors of Third-Party Seller(s)	P&E Costs	◔	○	○	●	●	◔	○	◔
2b	• Identify Needs of Existing Third-Party Seller(s) • Handle Third-Party Seller Inquiries	S&I Costs	◑	◑	◑	◑	●	○	●	◑
3	Operating Enterprise ⇔ Consumers									
3a	• Personalize Customer Communication • Analyze & Plan Marketing Activities	S&I Costs	●	◔	○	○	○	◔	◑	◔
3b	• Optimize Marketing Activities	B&D Costs	○	○	○	○	○	●	●	○
4	Self-operated Business ⇔ Suppliers									
4a	• Analyze Goods Movement	S&I Costs	◔	●	○	○	○	○	○	○
4b	• Optimize Goods Movement	B&D Costs	○	●	◑	○	○	○	◑	◑
5	Self-operated Business ⇔ Consumers									
5a	• Forecast Product Demand • Analyze Goods Movement (incl. Returns)	S&I Costs	◑	●	◑	○	◑	◑	○	○
5b	• Ensure Product Availability • Ensure Attractive Sales Conditions	B&D Costs	◑	●	◑	○	○	○	○	○
6	Self-Operated Business ⇔ Platform Business									
6	• Define Product Assortment • Ensure Competitive Product Pricing	B&D Costs	○	●	○	○	○	○	◕	◕
[…] Data For #7a, 7b, 8, and 9 is Not Displayed in This Short Paper										

Legend: S&I = Search & Information; B&D = Bargaining & Decision; P&E = Policing & Enforcement || E = Estimate, F = Forecast, C = Compare, D_E= Detect, I = Identify, D_i= Discover, G = Generate, A = Act || Harvey Balls Indicate Presence of High-Level AI Capability in Use Case Cluster by Frequency. ● = Very Strong, ◕ = Strong, ◑ = Moderate, ◔ = Low, ○ = None

Table 3. AI Use Case Clusters, Transaction Cost Effect and AI Capabilities Used per Transaction Relationship in OTTO's Hybrid Retail Platform Business (Excerpt).

Discussion & Next Steps

As outlined in the introduction, the aim of this ongoing research project is to help (re)direct scholarly attention to the *actual use* and *business value* of AI in electronic markets. Based on my preliminary findings, I envision to contribute to the existing literature in three key ways.

First, I seek to present a context-sensitive lens for analyzing the use of AI in platform-based businesses. By combining transaction cost theory (Coase, 1937; Williamson, 1971, 2010) with a taxonomy of high-level AI capabilities (Yildirim et al., 2023), I aim to operationalize value creation not simply as cost reduction, but as the outcome of AI use situated in specific *relational*, *processual*, and *functional* contexts. This three-dimensional perspective supports more granular theorizing by allowing researchers to distinguish the economic functions of AI use cases beyond broad categories. Initial findings suggest that even when AI use cases reduce the same type of transaction cost, they may rely on different AI capabilities depending on the *relational* and *processual* context in which they are applied.

Second, I seek to contribute to the discourse on transactional and relational foci in electronic market segments. My preliminary findings suggest that AI is primarily used to reduce search and information costs in business-to-consumer, and policing and enforcement costs in business-to-business relationships. Which is consistent with Malone et al. (1987) and later refinements by (Glassberg & Merhout, 2007). However, my initial findings also point to potential dynamics between business-to-business and business-to-consumer segments. For example, competitive dynamics introduced by third-party sellers can influence assortment and pricing decisions on the consumer side - decisions that are increasingly supported by AI. These interactions suggest that while transactional and relational segments may be analytically distinct, they may not be independent.

Third, I seek to offer empirical insight into the actual use of AI from "within" a major platform organization. While early theories anticipated that AI would reduce transaction costs in electronic markets (Malone et al., 1987), few studies have examined how this plays out in business practice. My case study of 66 AI use cases at OTTO provides concrete, contextualized examples from a leading European platform, thereby expanding the empirical base beyond the U.S. and Chinese firms that dominate the existing literature (Bawack et al., 2022).

This research-in-progress is limited by its preliminary stage, single-case focus, and point-in-time perspective. As next steps, I plan to employ more sophisticated methods to relate (combinations of) high-level AI capabilities to transaction cost effects (e.g., by qualitative comparative analysis) and refine the preliminary AI use case clusters. Future work is also likely to include substantiating the initial findings with interviews of key decision-makers. Hence, I will be able to present more data and advanced analysis results by the time of the conference.

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