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# Analiza determinantów przepływów handlowych na świecie w latach 2000–2020 z wykorzystaniem modeli grawitacyjnych

## Streszczenie

Niniejsza praca ma na celu sprawdzenie czynników wpływających na wielkość przepływów handlowych pomiędzy dwoma państwami. Wykorzystano do tego rozszerzony model grawitacyjny oraz następujące narzędzia ekonometryczne: modele Fixed Effects (FE), Correlated Random Effects (CRE) oraz Poisson Fixed Effects (PFE), szacowany metodą Poisson Pseudo Maximum Likelihood (PPML). Każdy model uzasadniono teoretycznie oraz dołączono do pracy replikowalne kody w R do sprawdzenia poprawności obliczeń. Zweryfikowano następujące hipotezy: 1) tradycyjne zmienne (PKB eksportera i importera oraz odległość między państwami) są istotnymi predykatorami poziomu handlu; 2) zamożność społeczeństwa mierzona PKB per capita pozytywnie wpływa na wymianę handlową; 3) wspólna granica zwiększa handel; 4) należenie państwa

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do Unii Europejskiej pozytywnie wpływa na jego eksport; 5) wspólny język i historia (przeszłość kolonialna) pozytywnie wpływają na wzajemny handel; oraz 6) podobieństwo systemów prawnych zwiększa wymianę handlową. Wykazano, że nie ma podstaw do odrzucenia hipotez 2), 3), 5) i 6). Analiza wpływu odległości na handel oraz członkostwa importera w UE jest bardziej zniuansowana.

**Słowa kluczowe:** handel międzynarodowy, dane panelowe, model grawitacyjny handlu, model Poisson Fixed Effects, model CRE, model efektów stałych.
**JEL:** F14, C33, C51

# Analysis of Trade Flows' Determinants from 2000 to 2020 Using Gravity Models

## Summary

This study aims to examine the factors influencing the volume of trade flows between two countries. An extended gravity model was utilized along with the following econometric tools: Fixed Effects (FE), Correlated Random Effects (CRE), and Poisson Fixed Effects (PFE) estimated with Poisson Pseudo Maximum Likelihood (PPML). Each model was theoretically justified, and replicable R codes were included to enable the correctness of the calculations to be checked. The study tested the following hypotheses: 1) traditional variables (GDP of the exporter and importer, as well as the distance between countries) are significant predictors of trade levels; 2) societal wealth, measured by GDP per capita, positively influences trade; 3) a shared border increases trade; 4) membership in the European Union positively impacts a country's exports; 5) a common language and shared history (colonial ties) positively influence bilateral trade; and 6) similarity in legal systems increases trade exchange. The analysis confirmed that there is no basis for rejecting hypotheses 2), 3), 5), and 6). The impact of distance on trade and the importer's EU membership proved to be more nuanced.

**Keywords:** international trade, panel data, gravity model of trade, Poisson Fixed Effects model, Correlated Random Effects, Fixed Effects.

# Wstęp

Modele grawitacyjne to niezwykle użyteczne narzędzie do analizowania determinantów handlu. W literaturze spotyka się artykuły wykorzystujące ten model w odniesieniu do jednego państwa (Cieślik 2018; Ambroziak 2018), członków organizacji międzynarodowej (Drzewoszewska i in. 2013; Maciejewski 2017; Pietrzak i Łapińska 2014), państw z określonego regionu świata (Golovko, Sahin 2021; Klimczak 2015), a nawet do jednostek administracyjnych w ramach jednego państwa (Mroczek i in. 2014). Tematycznie model grawitacyjny handlu wykorzystywany jest zazwyczaj do analizowania ogółu przepływów handlowych między państwami, aczkolwiek coraz częściej badacze skupiają się na jednym sektorze dóbr, np. rolniczych (Sapa, Droždz 2019) lub żywieniowych (Sapa, Kryszak 2021), albo nawet na pojedynczym dobrze, np. zbożu (Kułyk, Augustowski 2018) czy miodzie pszczelim (Popovych 2018).

Od strony praktycznej przeprowadzenie poprawnie metodologicznego badania ekonometrycznego z zastosowaniem powyższego modelu nie jest oczywiste. Najpopularniejsza analiza, która brałaby pod uwagę zarówno przekrojowy, jak i czasowy aspekt analizowanych danych, wymagałaby oszacowania modelu panelowego. Jako że analizie poddaje się całą populację (wszystkie województwa Polski, wszystkich członków Unii Europejskiej itp.), a nie losowo wybraną próbkę, to wskazane byłoby skorzystanie z modelu efektów stałych – ang. Fixed Effects – FE (Baltagi 2021, s. 12). Podejście to obarczone jest jednak pewnymi problemami. Po pierwsze, modelem FE nie można szacować wpływu czynników stałych w czasie na zmienną objaśnianą. Po drugie, przy stosowaniu logarytmów zmiennych wskazane jest wykluczenie obserwacji zawierających zerowe wartości (brak handlu pomiędzy dwoma państwami), co jednak wiąże się z arbitralnym założeniem, że zerowe obserwacje nie niosą żadnej istotnej wiadomości do modelu.

W pracy zaprezentowano dwa sposoby na rozwiązanie powyższych problemów. Poza modelem Fixed Effects (FE) zastosowano Correlated Random Effects (CRE) i Poisson Fixed Effects (PFE) będący szacowaniem modelu FE metodą Poisson Pseudo Maximum Likelihood (PPML). Modele oszacowano w programie R, a wszystkie zawarte w artykule obliczenia są w pełni replikowalne. Kody i dane udostępnione są w otwartym repozytorium: https://github.com/tymoteuszmetrak/gravity_article.

Poza problemami natury ekonometrycznej zajęto się weryfikacją kilku hipotez badawczych dotyczących determinantów handlu międzynarodowego. Sformułowano je na podstawie dotychczasowej literatury, biorąc pod uwagę zwłaszcza zmienne „typowego modelu grawitacyjnego” zaproponowane przez Heada i Mayera (2014) oraz główne przeszkody handlowe zebrane przez Bergstranda i Eggera (2013). W dalszej części artykułu znajduje się szersze omówienie badań będących podstawą stawianych hipotez. Weryfikacja niektórych z nich nie byłaby możliwa bez zastosowania modeli CRE i PFE. Badane hipotezy to:

- H1: tradycyjne zmienne (PKB eksportera, importera i odległość między państwami) są istotnymi predykatorami poziomu handlu;
- H2: zamożność społeczeństwa mierzona PKB per capita pozytywnie wpływa na wymianę handlową;
- H3: wspólna granica zwiększa handel;
- H4: należenie państwa do Unii Europejskiej pozytywnie wpływa na jego eksport;
- H5: wspólny język i historia (przeszłość kolonialna) pozytywnie wpływają na wzajemny handel;
- H6: podobieństwo systemów prawnych zwiększa wymianę handlową.

# 1. Model grawitacyjny – teoria

Socjolodzy i ekonomiści od co najmniej XIX w. zaczęli aplikować prawo powszechnego ciążenia Newtona do modelowania zjawisk społecznych. Jak podaje Chojnicki (1966), analizowano w ten sposób zwłaszcza migracje, popyt i podaż na produkty pomiędzy ośrodkami miejskimi oraz „siłę przyciągania" konsumentów do miast. Jednak to przede wszystkim wykorzystanie modelu grawitacyjnego do analizy handlu światowego trwale wpisało się do kanonu badań ekonomicznych.

Model grawitacyjny handlu w podstawowej formie cechuje się dużą prostotą oraz intuicyjnością. Zakłada on, że wielkość wymiany handlowej między państwami jest wprost proporcjonalna do wielkości ich gospodarek (wyrażonych zwykle jako PKB) i odwrotnie proporcjonalna do odległości (Tinbergen 1962). Można go przedstawić jako:

$$T_{i,j} = \frac{Y_i * Y_j}{D_{i,j}},$$

gdzie:
$T_{i,j}$ – wielkość wymiany handlowej między państwem *i* oraz *j*,
$Y_i$ – PKB państwa *i*,
$Y_j$ – PKB państwa *j*,
$D_{i,j}$ – dystans pomiędzy państwami *i* oraz *j*.

Model taki nie pozwala jednak na analizę wpływu innych czynników na wielkość wymiany handlowej, a także czyni kilka założeń, m.in., że koszty handlowe zależą wyłącznie od odległości dwóch państw, a podaż i popyt na dobra są zależne wyłącznie od wielkości gospodarek. Po uchyleniu tych założeń można szacować model postaci:

$$T_{i,j} = G_{i,j} * \frac{Y_i * Y_j}{D_{i,j}} * \ x_{1,i} * x_{1,j} * \dots * x_{k,i} * x_{l,j} * z_1 * \dots * z_n =$$
$$= G_{i,j} * \frac{Y_i * Y_j}{D_{i,j}} * X_{i,j} \quad ,$$

gdzie:
$G_{i,j}$ – to tzw. stała grawitacyjna – stała dla danego połączenia handlowego,
$x_{k,i}$ – k-ta zmienna wpływająca na handel $i$,
$x_{l,j}$ – l-ta zmienna wpływająca na handel $j$,
$z_n$ – n-ta zmienna wpływająca na wzajemny handel między $i$ oraz $j$,
$X_{i,j}$ – wektor zmiennych wpływających na handel $i$, lub handel $j$, lub handel między $i$ oraz $j$.

Istnieją jeszcze bardziej zaawansowane modele: strukturalny model grawitacyjny, modele z CES funkcją popytu itp. Istotny przegląd literatury w tym temacie przeprowadził Anderson (2011). Jednakże już dzięki powyższej modyfikacji tradycyjnego modelu grawitacyjnego handlu można szacować wpływ na handel takich zmiennych, jak wspólna granica, należenie do Unii Europejskiej, poziom PKB per capita i inne.

## 2. Przegląd literatury

Modele grawitacyjne handlu są jednymi z kilku popularnych modeli ekonometrycznych, służących do analizy handlu międzynarodowego. Warto wspomnieć chociażby o modelach Ricardo, Heckschera-Ohlina, Krugmana czy Dixita-Stiglitza. Pomimo takiej różnorodności dostępnych narzędzi model grawitacyjny pozostaje użyteczny; do takich wniosków doszedł ostatnio m.in. Klimczak (2015). Ogromnymi zaletami tego modelu są prostota i możliwość elastycznego kształtowania założeń co do funkcji konsumpcji.

Głównym zagadnieniem w odniesieniu do badanych modeli grawitacyjnych są determinanty przepływów handlowych. Przykładowo, Maciejewski i Wach (2019) dla państw Unii Europejskiej wykazali, że pozytywnie na handel wpływają PKB eksportera i importera, wspólna granica oraz członkostwo pary krajów w UE. Posiadanie wspólnej waluty euro na handel oraz PKB per capita eksportera miało nieoczywisty wpływ na handel. W ich badaniu odległość oddziaływała na handel negatywnie w sposób istotny statystycznie. Golovko i Sahin (2021) oszacowali modele PFE dla 86 państw Euroazji. Wykazali, że posiadanie wspólnej granicy i posługiwanie się tym samym językiem istotnie statystycznie zwiększa wzajemny handel między państwami. W ich modelach oszacowania przy logarytmie PKB per capita eksportera i importera były pozytywne i istotne statystycznie, tak samo jak należenie do Światowej Organizacji Handlu i regionalnych porozumień handlowych.

Liczba artykułów w analizowanym temacie w literaturze anglojęzycznej jest tak duża, że warto odwołać się do opracowań zbiorczych. W swoim artykule przeglądowym Kepaptsoglou i in. (2010) zwrócili uwagę, że w pierwszej dekadzie XXI w. jednym z najczęściej analizowanych tematów za pomocą modeli grawitacyjnych były efekty porozumień o wolnym handlu. Wyniki badań nie były zgodne, aczkolwiek pewna ich część zidentyfikowała pozytywny wpływ porozumień o wolnym handlu (np. NAFTA, UE, ASEAN) na wymianę handlową wewnątrz porozumienia i relatywny jej spadek z partnerami zewnętrznymi. Bergstrand i Egger (2013) skupili się wprost na przeszkodach w handlu badanych modelami grawitacyjnymi. „Naturalne" przeszkody, które bezpośrednio wpływają na koszty transportu dóbr to, zdaniem autorów, m.in.: odległość, średni czas wymagany do transportu dóbr drogą morską, brak wspólnej granicy i brak dostępu do oceanu światowego. Przeszkody „sztuczne" to przede wszystkim cła i brak członkostwa w porozumieniach o wolnym handlu, ale też nadmierne wymogi regulacyjne. Obecność tych przeszkód lub ich intensywność (np. większa odległość, wyższe cała) negatywnie wpływa na handel wzajemny między państwami.

Prawdopodobnie największą metaanalizę dotyczącą modeli grawitacyjnych handlu przeprowadzili Head i Mayer (2014). Po przeanalizowaniu 159 artykułów zidentyfikowali tzw. „typowy model grawitacyjny". Z ich badań wynika, że zmienne, które najczęściej pozytywnie wpływały na wielkość wzajemnej wymiany handlowej, to PKB importera i eksportera, wspólna granica, posługiwanie się tym samym językiem, powiązania kolonialne, istnienie porozumienia o wolnym handlu, członkostwo w UE, członkostwo w NAFTA oraz posługiwanie się tą samą walutą. Negatywnie na handel oddziaływała odległość między państwami.

Podobne wnioski płyną z literatury polskojęzycznej. Warto przytoczyć jednak kilka badań. Drzewoszewska i in. (2013) przeanalizowali wymianę handlową między państwami Unii Europejskiej w latach 1999–2010. W ich modelu PKB eksportera i importera pozytywnie wpływały na handel, a odległość negatywnie. Klimczak (2015) w analizie państw Bałkanów Zachodnich pokazał pozytywny wpływ PKB eksportera oraz jego populacji na handel. Co ciekawe, w jego badaniu PKB importera miało negatywny wpływ na handel, podobnie jak jego populacja i odległość fizyczna między państwami. Współczynnik przy odległości zmieniał jednak znak po dodaniu do modelu innych zmiennych, oddających bliskość językową, religijną, występowanie wspólnej granicy i stan wojny między krajami. Wojna wpływała negatywnie na wymianę handlową w danym roku oraz rok po zakończeniu, a pozostałe wymienione zmienne oddziaływały w sposób pozytywny. Cieślik (2007) zbadał wymianę handlową Polski z partnerami i wykazał pozytywny wpływ porozumień o wolnym handlu zarówno wielostronnych (Układ Europejski, EFTA i CEFTA), jak i bilateralnych (z Chorwacją, Estonią, Izraelem, Litwą, Łotwą, Estonią i Turcją) na wielkość wzajemnych obrotów handlowych. Co ciekawe, pozytywnie na wymianę wpływała też bliskość językowa (grupa języków słowiańskich). W badaniu powtórzonym dekadę później Cieślik (2018) oszacował pozytywny skutek dołączenia Polski do Unii Europejskiej na wielkość bilateralnych obrotów handlowych.

## 3. Dane

Do niniejszego badania wykorzystano powszechnie używaną bazę „CEPII – Gravity" (Conte, Cotterlaz, Mayer 2022). Zawiera ona dane dla 252 państw i terytoriów, które istniały na przestrzeni lat 1948–2021. Każdy wiersz w bazie oznacza przepływ handlowy pomiędzy państwem eksportera (*origin*) a importera (*destination*) w danym roku. Poza danymi odnośnie do handlu w bazie zebrano dane dotyczące odległości pomiędzy państwami (w tym odległościami ważonymi populacją), PKB, PKB per capita, populacji, posiadania wspólnej granicy, przeszłości kolonialnej, porozumień handlowych, uczestnictwa w Światowej Organizacji Handlu, posługiwania się tym samym językiem, posiadania wspólnie jednego państwa-przodka itd. Łącznie w bazie zebrano ponad 100 zmiennych, a liczba obserwacji przekracza 4 miliony.

W artykule ograniczono zakres czasowy do lat 2000–2020. Dla roku 2021 (najnowszego w bazie) obserwacje są niepełne i zawierają bardzo wiele brakujących wartości NA, dlatego zdecydowano się na ich usunięcie. Nie wzięto pod uwagę wartości sprzed roku 2000 z dwóch powodów. Po pierwsze, tam również znajdowało się wiele braków danych, co utrudniłoby analizę. Po drugie, to w czasach najnowszych popularna jest idea, że „odległość nie ma znaczenia" z powodu rozwoju technologii komunikacyjnych i informacyjnych. Zgodnie z hipotezą H1 dystans nadal powinien mieć znaczenie, a do jej weryfikacji potrzeba stosunkowo współczesnych danych. Odległość brana pod uwagę w niniejszym badaniu to tzw. dystans ważony populacją. Jest to wskaźnik odległości wyrażony w kilometrach, który bierze pod uwagę rozproszenie populacji w obu krajach i jest bardziej wiarygodny od indeksów, które mierzą odległość jedynie między stolicami lub między dwoma największymi miastami państw. Dystans ważony populacją bierze pod uwagę wszystkie miasta w danym kraju o populacji większej niż 300 000 osób[1] (Conte i in. 2022). Wyliczany jest według wzoru:

$$D_{i,j} = \left(\sum_{k\in i}\frac{pop_k}{pop_i} * \sum_{l\in j}\frac{pop_l}{pop_j} * {d_{kl}}^{-1}\right)^{-1},$$

gdzie:
$D_{i,j}$ – dystans między państwami ważony populacją,
$pop_k$ – populacja k-tego miasta w kraju $i$,
$pop_l$ – populacja l-tego miasta w kraju $j$,
$pop_i$ – suma populacji wszystkich dużych miast w państwie $i$,
$pop_j$ – suma populacji wszystkich dużych miast w państwie $j$,
$d_{kl}$ – odległość między miastem $k$ oraz $l$.

[1] Wartość 300 000 mieszkańców nie jest ustalona arbitralnie, a pochodzi z opracowania Organizacji Narodów Zjednoczonych, która tak właśnie definiuje duże miasto (World Urbanization Prospects 2018).

Dzięki takim przekształceniom zmienna odpowiadająca za odległość bierze pod uwagę rozproszenie populacji i jej strukturę geograficzną. Przykładowo, odległość między największymi miastami Polski i Niemiec (Berlin i Warszawa) wynosi 518 km, a dystans ważony populacją między oboma państwami w 2020 r. wyniósł 575 km.

W ramach dalszych przekształceń z otrzymanej bazy usunięto obserwacje, w których odzwierciedlony był handel państwa samego ze sobą (np. metropolii z własnym terytorium zamorskim). Usunięto też obserwacje, dla których brakowało danych co do PKB, odległości, danych o wspólnej granicy, języku i należenia do UE. Następnie podzielono bazę na dwie tabele – jedną, z której usunięto połączenia handlowe, dla których handel wynosił zero i jedną, w której takie wartości zostały zachowane. Potem zostawiono w obu bazach tylko te połączenia handlowe, dla których dostępne są pełne dane za lata 2000–2020, aby otrzymać zbilansowany panel. Na sam koniec wyliczono logarytmy wybranych zmiennych – PKB, PKB per capita i odległości ważonej populacją.

## 4. Wykorzystane modele

Łącznie oszacowano pięć modeli opisanych poniżej. Pierwsze dwa są modelami bazowymi, które napotykają na dwie podstawowe trudności – niemożliwość szacowania wpływu regresorów stałych w czasie oraz konieczność pominięcia w modelowaniu obserwacji, dla których wielkość wymiany handlowej wynosi 0. Kolejne modele odpowiadają na te trudności i rozwiązują je.

### Model 1

Podstawowy model, którego użyto, to model efektów stałych dla każdego połączenia handlowego – model FE. Model taki wymaga addytywnej formy, dlatego konieczne było przekształcenie powyżej omówionego równania poprzez obustronne zlogarytmowanie. Oszacowano zatem model podstawowy postaci:

$$\ln\left(T_{i,j}\right) = \ln\left(G_{i,j}\right) + \alpha_1 \ln(Y_i) + \alpha_2 \ln\left(Y_j\right) + \alpha_3 \ln\left(D_{i,j}\right) + u_{i,j},$$

gdzie $u_{i,j}$ to egzogeniczny składnik losowy (który może być skorelowany z jakimkolwiek regresorem).

Zgodnie z hipotezami oczekuje się, że współczynniki $\alpha_1$ i $\alpha_2$ będą dodatnie na poziomie istotności 5%, a $\alpha_3$ przyjmie wartość istotnie ujemną.

### Model 2

Aby przetestować pozostałe hipotezy, konieczne było rozszerzenie modelu o dodatkowe zmienne zależne. Oszacowano model postaci:

$$\ln(T_{i,j}) = \ln(G_{i,j}) + \alpha_1 \ln(Y_i) + \alpha_2 \ln(Y_j) + \alpha_3 \ln\left(Y_{cap_i}\right) + \alpha_4 \ln\left(Y_{cap_j}\right) +$$
$$+\alpha_5 \ln(D_{i,j}) + \alpha_6 \mathrm{EU}_i + \alpha_7 \mathrm{EU}_j + \alpha_8 \mathrm{B}_{i,j} + \alpha_9 \mathrm{L}_{i,j} + \alpha_{10} \mathrm{Com}_{\mathrm{col}_{i,j}} +$$
$$+\alpha_{11} \mathrm{Col\_45}_{i,j} + \alpha_{12} Legal_{i,j} + u_{i,j}$$

gdzie:
$\ln(Y\_cap_i)$ – logarytm PKB per capita w państwie eksportera,
$\ln(Y\_cap_j)$ – logarytm PKB per capita w państwie importera,
$\mathrm{EU}_i$ – zmienna binarna, czy państwo eksportera należało w danym roku do UE,
$\mathrm{EU}_j$ – zmienna binarna, czy państwo importera należało w danym roku do UE,
$\mathrm{B}_{i,j}$ – zmienna binarna, czy państwa posiadają wspólna granicę,
$\mathrm{L}_{i,j}$ – zmienna binarna, czy przynajmniej część populacji obu państw mówi tym samym językiem,
$\mathrm{Com\_col}_{i,j}$ – zmienna binarna, czy oba państwa miały wspólnego kolonizatora po 1945 r.,
$\mathrm{Col\_45}_{i,j}$ – zmienna binarna, czy oba państwa znajdowały się w relacji kolonialnej po 1945 r.,
$Legal_{i,j}$ – zmienna binarna, czy państwa mają wspólne źródła systemu prawnego.

Powyższy model zawiera jednak dwa problemy. Po pierwsze, niemożliwe jest oszacowanie wpływu zmiennych stałych na zmienną objaśniająca z powodu procedury „uśredniania”. Przykładowo, dla Modelu 1 proces szacowania będzie przebiegał następująco. Najpierw należy obliczyć średnie (po czasie) wszystkich zmiennych po obu stronach równania:

$$\overline{\ln(T_{i,j})} = \overline{\ln(G_{i,j})} + \alpha_1 \overline{\ln(Y_i)} + \alpha_2 \overline{\ln(Y_j)} + \alpha_3 \overline{\ln(D_{i,j})} + \overline{u_{i,j}}.$$

Odejmując teraz to równanie od pierwotnego:

$$\ln(T_{i,j}) - \overline{\ln(T_{i,j})} = \left(\ln(G_{i,j}) - \overline{\ln(G_{i,j})}\right) + \alpha_1\left(\ln(Y_i) - \overline{\ln(Y_i)}\right) +$$
$$+\alpha_2 \left(\ln(Y_j) - \overline{\ln(Y_j)}\right) + \alpha_3 \left(\ln(D_{i,j}) - \overline{\ln(D_{i,j})}\right) + (u_{i,j} - \overline{u_{i,j}}),$$

gdzie $\ln(G_{i,j}) = \overline{\ln(G_{i,j})}$, bo stała jest ze swojej natury stała w czasie. Ich różnica wyniesie zatem zero. Tak samo w procesie uśredniania stanie się z innymi zmiennymi stałymi w czasie. Finalny model, szacowany w modelu efektów stałych (stosując notację, że $\ddot{x} = x - \bar{x}$), będzie miał postać:

$$\ln(\ddot{T}_{i,j}) = \alpha_1 \ln(\ddot{Y}_i) + \alpha_2 \ln(\ddot{Y}_j) + \alpha_3 \ln(\ddot{D}_{i,j}) + \ddot{u}_{i,j}.$$

Drugi problem dotyczy logarytmowania zmiennej niezależnej. Poprzez zlogarytmowanie zmiennej „handel” zmuszeni jesteśmy bowiem wyłączyć z naszej próby wszystkie połączenia handlowe, dla których handel był zerowy. Może mieć to wpływ na oszacowania, gdyż stosując takie modele zakłada się *a priori*, że zerowy eksport jednego państwa do drugiego nie niesie ze sobą żadnych informacji.

## Model 3

Rozwiązaniem problemu nr 1, czyli szacowania wpływu zmiennych stałych w czasie, może być model CRE – Correlated Random Effects. Dopuszcza on korelację błędu ze zmiennymi objaśniającymi, a jednocześnie pozwala na otrzymanie oszacowań dla zmiennych stałych w czasie. Oszacowania dla pozostałych zmiennych są identyczne jak w modelu FE (Wooldridge 2021). W praktyce takie estymacje otrzymuje się dzięki dodaniu średnich zmiennych w czasie do modelu i późniejsze szacowanie modelu RE. To pozornie proste przekształcenie zostało zaproponowane niezależnie od siebie przez Mundlaka (1978) i Chamberlaina (1984), ale dopiero od niedawna zyskuje na popularności. Szacowany model będzie miał postać:

$$
\begin{gathered}
\ln\left(T_{i,j}\right) = \ln\left(G_{i,j}\right) + \alpha_1 \ln(Y_i) + \alpha_2 \ln\left(Y_j\right) + \alpha_3 \ln\left(Y_{cap_i}\right) + \alpha_4 \ln\left(Y_{cap_j}\right) + \\
+\alpha_5 \ln\left(D_{i,j}\right) + \alpha_6 \mathrm{EU}_i + \alpha_7 \mathrm{EU}_j + \alpha_8 \mathrm{B}_{i,j} + \alpha_9 \mathrm{L}_{i,j} + \alpha_{10} \mathrm{Com}_{\mathrm{col}_{i,j}} + \\
+\alpha_{11} \mathrm{Col}_{45_{i,j}} + \alpha_{12} Legal_{i,j} + \alpha_{13} \overline{\ln(Y_i)} + \alpha_{14} \overline{\ln\left(Y_j\right)} + \alpha_{15} \overline{\ln\left(D_{i,j}\right)} + \\
+ \alpha_{16} \overline{\ln\left(Y_{cap_i}\right)} + \alpha_{17} \overline{\ln\left(Y\_cap_j\right)} + \alpha_{18} \overline{\mathrm{EU}_i} + \alpha_{19} \overline{\mathrm{EU}_j} + u_{i,j}
\end{gathered}
$$

Dotychczas w literaturze polskojęzycznej jako rozwiązanie powyższego problemu wskazywano oszacowanie modelu Hausmana-Taylora (por. Bułkowska 2018, s. 44). Wykorzystali go m.in. Cieślik i Hagemejer (2011), zajmując się kwestią liberalizacji handlu w Europie Środkowej i Wschodniej, oraz Cieślik i in. (2009), badając potencjalne skutki przystąpienia Polski do strefy euro. Model Hausmana-Taylora (1981) zakłada podział zmiennych objaśniających na dwie kategorie: 1) te, które mogą być skorelowane z efektem indywidualnym, oraz 2) te, które na pewno są z nim nieskorelowane. W obu tych grupach mogą pojawić się zmienne stałe w czasie. W celu estymacji współczynników model stosuje najpierw model efektów stałych (FE), aby oszacować część parametrów i uzyskać reszty. Następnie używana jest metoda zmiennych instrumentalnych do estymacji pozostałych parametrów. Dotychczasowe oszacowania parametrów umożliwiają obliczenie reszt, które są z kolei wykorzystywane do wyznaczenia wariancji błędu losowego oraz efektu indywidualnego. Dzięki temu możliwe jest zastosowanie metody najmniejszych kwadratów z korektą (UMNK) w celu uzyskania końcowych estymacji (StataCorp 2023). Poprawne wykorzystanie tego modelu wymaga dużej wiedzy eksperckiej i starannego dopasowania zmiennych do ww. grup. Model CRE nie posiada tych ograniczeń, a ponadto jego oszacowania są łatwo porównywalne z modelem FE.

## Modele 4 i 5

Rozwiązaniem problemu nr 2, czyli ograniczenia się do dodatnich wartości handlu, może być model efektów stałych szacowany z rozkładem Poissona – Poisson Fixed Effects (PFE). W literaturze taki sposób estymacji nazywa się Poisson

Pseudo-Maximum Likelihood (PPML). Jest to rozszerzenie zwykłego modelu Poissona na dane panelowe. Zmienną objaśnianą jest poziom handlu bez logarytmowania, przez co można wykorzystać zdecydowanie więcej obserwacji. Otrzymane oszacowania są zgodne, a interpretacja oszacowań taka jak w modelach szacowanych MNK – dla zmiennych objaśnianych w logarytmie współczynnik jest elastycznością, a dla zmiennych binarnych jest semielastycznością (Shepherd i in. 2019). Przedstawiając skrótowo, model przyjmuje postać:

$$E\left(T_{i,j}|X\right) = \delta_{i,j} * e^{\theta' X},$$

gdzie $\delta_{i,j}$ to efekt stały (por. stałą grawitacyjną dla połączenia handlowego), $\theta$ to wektor współczynników, a $X$ to wektor niestałych w czasie zmiennych objaśniających.

Analogicznie do modelu FE modele PFE też oszacowano w wersji podstawowej (Model 4 tylko z 3 regresorami – logarytmy PKB i odległości) i rozszerzonej (Model 5).

## 5. Badanie empiryczne

Wyniki oszacowań modelu podstawowego Fixed Effects i Poisson Fixed Effects (Modele 1 i 4) zawiera tabela 1. W obu modelach PKB eksportera i importera pozytywnie wpływają na handel pomiędzy państwem eksportera a importera.

**Tabela 1.** Wyniki oszacowań Modeli 1 i 4

| | **FE (1)** | **PFE (4)** |
|---|---|---|
| Log. PKB eksportera | $0{,}53^{***}$ (0,01) | $0{,}50^{***}$ (0,00) |
| Log. PKB importera | $0{,}77^{***}$ (0,01) | $0{,}54^{***}$ (0,00) |
| Log. odległości | –0,22 (0,17) | $-0{,}53^{***}$ (0,00) |
| Liczba obserwacji | 291543 | 589176 |
| $R^2$ | 0,25 | |
| Adj. $R^2$ | 0,21 | |
| Log Likelihood | | –9050369788,35 |
| AIC | | 18100739582,70 |

Objaśnienia: $^{***}p < 0{,}001$; $^{**}p < 0{,}01$; $^{*}p < 0{,}05$.

Źródło: opracowanie własne.

Jak widać, w modelu efektów stałych co prawda współczynnik przy odległości ma oczekiwany znak, jednakże nie jest on istotny statystycznie. W modelu PFE odległość ma wpływ ujemny i istotny statystycznie na poziomie 0,1%. Różnica we wpływie odległości może wynikać z dwóch powodów. Po pierwsze, model PFE został oszacowany na prawie 2 razy większej liczbie obserwacji niż model FE, gdyż model FE nie mógł zawierać żadnych obserwacji, dla których poziom handlu wynosił zero. Drugi powód podnoszą Shepherd i in. (2019), stwierdzając, że w modelach grawitacyjnych szacowanych MNK reszty w modelu ulegają specjalnej heteroskedastyczności, związanej z przekształceniem logarytmicznym zmiennych. Niestety zastosowanie macierzy odpornych nie niweluje tych problemów. Oceniając wpływ odległości na wzajemny handel między państwami należy raczej skupić się na oszacowaniach modelu PFE.

**Tabela 2.** Wyniki oszacowań Modeli 2, 3 i 5

| | **FE (2)** | **CRE (3)** | **PFE (5)** |
|---|---|---|---|
| Stała | | –16,99*** (0,24) | |
| Log. PKB eksportera | 0,39*** (0,02) | 0,39*** (0,02) | 0,19*** (0,00) |
| Log. PKB importera | 0,68*** (0,02) | 0,68*** (0,02) | 0,36*** (0,00) |
| Log. PKB per capita eksportera | 0,16*** (0,02) | 0,16*** (0,02) | 0,34*** (0,00) |
| Log. PKB per capita importera | 0,09*** (0,02) | 0,09*** (0,02) | 0,22*** (0,00) |
| Log. odległości | –0,18 (0,17) | –0,18 (0,17) | –0,28*** (0,00) |
| Eksporter członkiem UE | 0,33*** (0,02) | 0,33*** (0,02) | 0,32*** (0,00) |
| Importer członkiem UE | –0,04* (0,02) | –0,04* (0,02) | 0,12*** (0,00) |
| Wspólna granica | | 0,99*** (0,09) | |
| Wspólny język | | 0,48*** (0,04) | |
| Wspólny kolonizator | | 0,99*** (0,05) | |
| Powiązania kolonialne po 1945 | | 0,98*** (0,11) | |
| Wspólne źródła systemu prawnego | | 0,12*** (0,03) | |
| Between(lnGDP_o) | | 0,72*** (0,02) | |
| Between(lnGDP_d) | | 0,20*** (0,02) | |
| Between(lnGDP_cap_o) | | –0,09*** (0,03) | |
| Between(lnGDP_cap_d) | | –0,06* (0,03) | |

| | | | |
|---|---|---|---|
| Between(lnDIST) | | –0,99*** (0,17) | |
| Between(eu_o) | | –0,37*** (0,04) | |
| Between(eu_d) | | –0,15*** (0,04) | |
| Liczba obserwacji | 291543 | 291543 | 589176 |
| $R^2$ | 0,25 | 0,32 | |
| Adj. $R^2$ | 0,21 | 0,32 | |
| Log Likelihood | | | –9394974978,94 |
| AIC | | | 18789949971,88 |

Objaśnienia: ***p < 0,001; **p < 0,01; *p < 0,05.

Źródło: opracowanie własne.

Oszacowanie najpełniejszego modelu CRE, w którym ujęto zmienne stałe w czasie, przedstawia tabela 2. Zawarto w niej również odpowiadające modelowi CRE modele FE i PFE rozszerzone o pozostałe zmienne, które nie są stałe w czasie. Co pierwsze rzuca się w oczy, to oszacowania Modelu 2 i Modelu 3 odnośnie do zmiennych, które nie są stałe w czasie, są identyczne zarówno co do ich wartości, jak i co do ich błędów standardowych. Model 3 zawiera ponadto efekty *between* dla zmiennych, które nie są stałe w czasie.

Analizując wpływ logarytmu PKB na eksport, to w Modelach 2, 3 i 5 rozmiar gospodarek zarówno eksportera, jak i importera mają pozytywny znak i są istotne statystycznie. Wpływ ten jest jednak wyraźnie mniejszy w oszacowaniach Modelu 5. Jednakże to w Modelu 5 (PFE) wpływ średniej zamożności społeczeństwa, czyli PKB per capita, jest silniejszy niż w Modelach 2 i 3. W wszystkich modelach z tabeli 2 wpływ tych zmiennych jest jednak istotny statystycznie na poziomie 0,1%.

Zmienna logarytm odległości okazała się istotna statystycznie tylko w Modelu 5, a przyczyny tego muszą być podobne do tych opisanych powyżej, przy analizie oszacowań modeli „oszczędnych" tylko z 3 zmiennymi objaśniającymi (Modele 1 i 4).

Zastanawiające są też oszacowania wpływu członkostwa w Unii Europejskiej na poziom handlu pomiędzy państwami. Modele 2, 3 i 5 zgodnie wskazują, że jeśli państwo-eksporter jest członkiem UE, to eksportuje więcej niż gdyby nie było członkiem wspólnoty. Siła tego wpływu jest praktycznie identyczna w szacowanych modelach. Zostanie członkiem UE podnosi eksport o około $(e^{0,32} - 1) * 100\% \approx 37,72\%$ przy innych czynnikach niezmienionych. Wpływ członkostwa państwa importera w Unii Europejskiej nie jest jasny. Modele 2 i 3 sugerują, że nieznacznie zmniejsza to import (o około 4%). Jednakże Model 5 wskazuje, że ten wpływ jest pozytywny i wynosi około $(e^{0,12} - 1) * 100\% \approx 12,75\%$ przy innych czynnikach niezmienionych.

Teoretycznie można uzasadnić oba wyniki. Unia Europejska posiada wspólny system ceł oraz regulacji dotyczących importu. Standardy unijne dotyczące jakości produktów, zwłaszcza żywieniowych, są jednymi z najostrzejszych na świecie. Jednocześnie, dołączając do UE, inne państwa członkowskie nie są już objęte taryfami celnymi, więc mogą „wypychać" import z państw spoza wspólnoty.

Z drugiej strony dołączenie do UE wiąże się zazwyczaj ze wzrostem PKB i otrzymywaniem środków z Funduszu Spójności, co kolektywnie zwiększa poziom wydatków i powinno stymulować import w ogólności, nie tylko z państw wewnątrz UE. Z punktu widzenia ekonometrycznego problematycznym jest zidentyfikowanie przyczyn różnic oszacowań między Modelami 2 i 3 a 5. Może być to kwestia zdecydowanie szerszej próby przy estymacji Modelu 5. Wydaje się jednak, że dalsze badania są potrzebne w tym obszarze.

Zmienne stałe w czasie oszacowane Modelem 3 są istotne statystycznie i mają wartość dodatnią. Posiadanie wspólnej granicy zwiększa wzajemny handel średnio o około $(e^{0,98} - 1) * 100\% \approx 166,45\%$ przy innych czynnikach niezmienionych. Silny pozytywny wpływ mają też wspólny język używany przynajmniej przez część populacji obu państw. Ciekawym z punktu widzenia badań nad kolonializmem jest istotny statystycznie i bardzo silny wpływ zmiennych kolonialnych na handel wzajemny między państwami. Posiadanie wspólnego kolonizatora w przeszłości zwiększa wzajemny handel aż o około $(e^{0,99} - 1) * 100\% \approx 169,12\%$. Podobny wpływ ma zachowywanie powiązań kolonialnych pomiędzy dwoma państwami po 1945 r.

Zbliżone systemy prawne, rozumiane jako wspólne źródła obecnych porządków prawnych, również mają istotny statystycznie pozytywny wpływ na handel między dwoma państwami. Podobieństwo systemów prawnych zwiększa wymianę handlową między partnerami o około $(e^{0,12} - 1) * 100\% \approx 12,75\%$ przy innych czynnikach niezmienionych.

## 6. Wnioski i podsumowanie

W artykule zweryfikowano sześć postawionych we wstępie hipotez. Wykazano, że rzeczywiście PKB eksportera i importera są istotnymi predykatorami poziomu handlu (H1). Co ciekawe, oszacowane wartości współczynników przy tych zmiennych sugerują, że większy wpływ na wymianę handlową ma PKB importera. Model 5 sugeruje, że wzrost PKB eksportera o 1% zwiększy wymianę handlową średnio o $(e^{0,19} - 1) * 1\% \approx 0,21\%$, a PKB importera prawie 2 razy więcej – o $(e^{0,36} - 1) * 100\% \approx 0,43\%$. Podobne jakościowo wnioski wynikają z innych modeli. Kolejna tradycyjna zmienna – odległość między państwami – okazała się wpływać na poziom handlu w sposób nieoczywisty. Znaczenie odległości różniło się pomiędzy modelami, ale można z ostrożnością przyjąć (na podstawie Modeli 4 i 5 oszacowanych na większej próbie), że odległość wpływa negatywnie na handel w sposób istotny.

Pozytywnie zweryfikowano hipotezę H2, że zamożność społeczeństwa (mierzona poprzez PKB per capita) pozytywnie wpływa na wymianę handlową. W tym przypadku zamożność mieszkańców państwa eksportera ma większy wpływ niż importera, co wydaje się zaskakujące. Wzrost PKB per capita eksportera o 1% zwiększa wymianę handlową średnio o $(e^{0,34} - 1) * 1\% \approx 0,40\%$, podczas gdy importera o $(e^{0,22} - 1) * 1\% \approx 0,25\%$ (opierając się na Modelu 5).

Zgodnie z intuicją i literaturą wykazano również, że wspólna granica zwiększa poziom handlu między dwoma państwami, pozytywnie weryfikując hipotezę H3. Wpływ ten jest bardzo silny – posiadanie wspólnej granicy podwyższa handel średnio aż o $(e^{0,99} - 1) * 100\% \approx 169,12\%$.

Na podstawie Modelu 3 należy przyjąć także hipotezę H5. Posługiwanie się tym samym językiem przez obywateli obu państw zwiększa wzajemny handel średnio o $(e^{0,48} - 1) * 100\% \approx 61,61\%$. Niniejsze badanie potwierdza też znany trend ponadprzeciętnego poziomu handlu pomiędzy państwami europejskimi a ich koloniami (por. Kleiman 1976). Co ciekawe, wykazano, że handel pomiędzy koloniami, które w przeszłości były zależne od jednego mocarstwa, jest wyższy niż w przeciwnym przypadku. Kilkadziesiąt lat po uzyskaniu niepodległości zaszłości historyczne nadal mają znaczenie dla poziomu handlu.

Ponadto badanie stanowi argument, że zbliżone systemy prawne skutkują większą wymianą handlową pomiędzy dwoma państwami, co potwierdza prawdziwość hipotezy H6. Zależność ta jest jednak zdecydowanie słabsza od wpływu zmiennych politycznych (wspólny kolonizator), społecznych (wspólny język) i naturalnych (wspólna granica).

Nieoczywiste wnioski dotyczą zwłaszcza członkostwa w Unii Europejskiej (hipoteza H4). Potwierdzono w tym artykule, że obecność w UE państwa eksportera zwiększa jego eksport. Wpływ członkostwa na import jest jednak niejednoznaczny i wymaga dalszych badań.

Z punktu widzenia metodologii wartością dodaną pracy jest zwłaszcza to, że pokazano, iż warto stosować różne metody ekonometryczne do badania determinantów handlu. Modele CRE i PFE okazały się użytecznymi narzędziami do estymacji modeli grawitacyjnych handlu, rozwiązując problem zmiennych stałych w czasie oraz problem zerowych wartości zmiennej objaśnianej. Pozwoliło to na włączenie do analizy większej liczby zmiennych (modele CRE), a także więcej obserwacji (modele PFE). Wszystkie obliczenia zawarte w artykule są w pełni replikowalne i mogą stanowić inspirację dla kolejnych badaczy w innych projektach naukowych.

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# Working Capital Management Strategy Effects on Firm Profitability and Risk: An Analysis of Polish Listed Construction Companies

## Summary

The article presents an analysis of working capital management strategies in the construction sector in Poland. The main objective of the study is to examine the impact of working capital management on the profitability and risk of firms operating in this sector. The study covered a group of public companies from 2019 to 2023. A synthetic indicator was developed to provide a comprehensive assessment of working capital management strategies, taking into account both financing and investment aspects. Based on the research, four basic working capital management strategies were identified and characterized, analyzing their impact on companies' profitability and risk. Contrary to prevailing finance theory, the results indicate that in the construction sector, aggressive working capital management strategies negatively affect profitability while increasing

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operational risk. The study showed that the peculiarities of the construction sector, characterized by long project delivery cycles and significant capital intensity, require a more conservative approach to working capital management. The proposed methodology for evaluating working capital management strategies provides a useful tool to support decision-making in companies operating under increased market uncertainty.

**Keywords:** working capital management, profitability, construction sector, risk
**JEL:** G31, G32, G38, L79

# Wpływ strategii zarządzania kapitałem obrotowym na rentowność i ryzyko firmy: na przykładzie publicznych spółek sektora budownictwa w Polsce

## Streszczenie

W artykule przedstawiono analizę strategii zarządzania kapitałem obrotowym w sektorze budowlanym w Polsce. Głównym celem badania jest zidentyfikowanie wpływu zarządzania kapitałem obrotowym na rentowność i ryzyko firm działających w tym sektorze. Badaniem objęto grupę spółek publicznych w latach 2019–2023. Opracowano syntetyczny wskaźnik zapewniający kompleksową ocenę strategii zarządzania kapitałem obrotowym, uwzględniający zarówno aspekty finansowe, jak i inwestycyjne. Na podstawie badań zidentyfikowano i scharakteryzowano cztery podstawowe strategie zarządzania kapitałem obrotowym, analizując ich wpływ na rentowność i ryzyko spółek. W przeciwieństwie do dominującej teorii finansów, wyniki wskazują, że w sektorze budowlanym agresywne strategie zarządzania kapitałem obrotowym negatywnie wpływają na rentowność, jednocześnie zwiększając ryzyko operacyjne. Badanie wykazało, że specyfika sektora budowlanego, charakteryzująca się długimi cyklami realizacji projektów i znaczną kapitałochłonnością, wymaga bardziej

konserwatywnego podejścia do zarządzania kapitałem obrotowym. Zaproponowana metodologia oceny strategii zarządzania kapitałem obrotowym stanowi użyteczne narzędzie wspierające podejmowanie decyzji w firmach działających w warunkach zwiększonej niepewności rynkowej.

**Słowa kluczowe:** zarządzanie kapitałem obrotowym, rentowność, sektor budownictwa, ryzyko

## Introduction

Modern corporate financial management emphasizes the key role of working capital as the foundation for ensuring liquidity and optimizing financial performance. In particular, events such as the global financial crisis of 2008 (Carbo-Valverde et al., 2013) and the global COVID-19 pandemic (Lilas Demmou et al., 2021; Zimon and Tarighi, 2021) are a reminder that sustained shareholder value growth is built in an environment of full liquidity (Baker et al., 2023). This liquidity can be secured by an appropriate working capital management policy. The right strategy is one that maximizes the trade-off between profitability and risk (Van Horne and Wachowicz, 2009). Net working capital is defined as the difference between two aggregate balance sheet items, current assets and current liabilities (Sagner, 2014). However, beyond this accounting identity, net working capital can also be understood from a broader financial management perspective. As noted by Zietlow (2020), "short-term financial management refers to the utilization of the firm's current assets and liabilities to maximize shareholder wealth," with working capital encompassing cash and equivalents, accounts receivable, inventory, accounts payable, and accruals. These components, when grouped functionally, represent short-term operating and financial decisions that impact a firm's liquidity and operational continuity. In this context, working capital is not just a residual from the balance sheet, but a dynamic concept involving both investment and financing decisions. It includes both the assets committed to day-to-day operations and the liabilities used to finance them. Therefore, in this study, we focus separately on the two sides of working capital management: investment in current assets and financing via current liabilities. We will refer to current asset management as the investment strategy and short-term liability management as the financing strategy. The A1 variable corresponds to the degree of investment in current assets, while A2 captures the approach to financing these assets using short-term liabilities. While the terminology "financing of working capital" might seem ambiguous, it is consistent with the view that managing the composition and maturity of short-term liabilities is an essential part of the working capital strategy. The combined interaction of these two approaches will be referred to throughout the article as the working capital management strategy.

The Polish construction sector is a major component of Poland's GDP. In 2022, it reached a 10% share of the total national product and employs 6-8% of all employees in the Polish economy (The Polish Investment & Trade Agency, 2023). The construction sector is characterized by long project delivery cycles, significant dependence on external financing and a high risk of payment delays (Leśniak and Plebankiewicz, 2010). Under such conditions, working capital management becomes a key strategic challenge. Effective liquidity management not only enables companies to survive in a competitive market, but also contributes to improving their profitability (Sierpińska and Wędzki, 2017). On the other hand, wrong decisions in working capital management strategies can lead to a significant increase in operational risk and, in extreme cases, to bankruptcy (Hanlon et al., 2020).

Despite the wide range of literature on working capital management, there is still a need for empirical verification of the assumptions of classical theories regarding the impact of particular strategies on firm's profitability and risk. These theories suggest that aggressive strategies, which involve minimizing the level of net working capital, should lead to higher profitability while increasing risk, while conservative strategies (in our case referred to as defensive), which involve maintaining higher liquidity reserves, may reduce risk at the expense of lower profitability (Brigham and Houston, 2022; Neveu, 1989; Preve and Sarria-Allende, 2010; Sierpińska and Wędzki, 2017; Van Horne and Wachowicz, 2009). The aim of this article is to test whether these classical assumptions are confirmed by actual data on the Polish construction sector.

## 1. Literature review

The management of working capital has been a focal point of financial research for last decade, with numerous studies investigating its impact on corporate performance. A significant body of research underscores the critical role of working capital management in enhancing firm profitability. Ali and Ali (2012) demonstrate that effective working capital decisions positively influence organizational profitability by balancing liquidity and operational efficiency. Similarly, Raheman and Nasr (2007) find a strong negative relationship between the cash conversion cycle (a core working capital metric) and profitability in Pakistani firms, suggesting that shorter cycles enhance profitability. This aligns with findings from Deloof (2003), who shows that reducing days accounts receivable and inventory levels improves profitability for Belgian firms. For SMEs, Martínez-Solano and García-Teruel (2007) report similar benefits, as shorter cash conversion cycles and reduced inventory improve profitability in Spanish companies. These findings are confirmed by Makori and Jagongo (2013), who emphasize that both receivables and inventory management directly affect profitability, though the relationship with days payable is nuanced. Recent studies further reinforce these conclusions. For instance, Aldubhani et al. (2022) find that shorter cash conversion cycles and faster receivables collection enhance profitability across several metrics (ROA, ROE), while Amponsah-Kwatiah and Asiamah (2020) confirm that efficient inventory, receivables, and payables management supports firm performance in Ghana's manufacturing sector. Similar effects are noted by Thiago Alvarez et al. (2021) for Argentinian SMEs and by Sidra Tahir and Baloch (2023) for Pakistani manufacturing firms.

The choice of working capital management strategy significantly impacts firm outcomes. Korent and Orsag (2018) illustrate a concave relationship between net working capital and profitability, identifying an optimal level that maximizes returns. However, deviations from this level, either toward aggressive or conservative strategies, decrease profitability. Maswadeh (2015) finds that moderate strategies yield higher profitability compared to aggressive ones, while conservative approaches are rarely employed. Le (2019) highlights the trade-offs involved in working capital management, noting a negative relationship between net working capital and firm valuation, profitability, and risk. This trade-off underscores the strategic importance of managing liquidity and financial flexibility, especially for firms with limited capital access or during economic recoveries. This perspective is echoed in the findings of Akgün and Karataş (2020), who emphasize that elevated working capital levels negatively affect profitability, particularly in civil law countries and during crisis periods like 2008. Lefebvre (2022) adds that post-IPO firms often adopt more conservative working capital strategies, especially smaller firms or those without debt, highlighting the nuanced strategic adjustments firms make in varying financial contexts.

Working capital strategies vary across industries and economic contexts. Mielcarz, Osiichuk, and Wnuczak (2018) examine Polish firms, finding that during recessions, more profitable firms adopt conservative strategies, accumulating precautionary cash reserves. In contrast, Zimon (2020) observes that Polish manufacturing and tourism companies tend to favor moderate-conservative strategies, while transport and trade companies employ moderate-aggressive approaches. The COVID-19 crisis has demonstrated that SMEs should build financial reserves and adopt more conservative management strategies, prioritizing financial security over profit maximization. Complementing these observations, Rey-Ares et al. (2021) identify an optimal (U-shaped) level of inventories and receivables in Spanish fish canning companies, while longer payables periods reduce profitability. Further, sector-specific insights, such as those from Mohanty et al. (2023), show that in volatile industries like automotive, firms optimizing inventory and receivables achieve superior returns. Similarly, Eladly (2021) shows that liquidity ratios strongly influence profitability and asset quality in Egypt's insurance sector, though findings partly diverge from general industry patterns. Emerging research also highlights the role of digitalization in working capital efficiency. Gill et al. (2022) find that IT investments significantly shorten the cash conversion cycle and improve efficiency among Indian SMEs, particularly where owners are well-educated.

Despite the robust theoretical and empirical foundations, several gaps remain. Most studies focus on general manufacturing or service sectors, with limited attention to industry-specific dynamics, such as those in the construction sector. Furthermore, while the trade-offs between profitability and risk are well-documented, there is limited empirical evidence testing these relationships in the Polish corporate context. Additionally, the literature lacks comprehensive metrics for comparing working capital strategies across firms. This study addresses these gaps by introducing a novel, dual-perspective indicator that combines activity-based ratios (integrating income statement and balance sheet data) with balance-sheet-specific metrics (e.g., working-to-fixed capital ratio). The theoretical contribution lies in redefining working capital management strategies—traditionally viewed as qualitative and context-dependent—into a quantifiable framework, enhancing cross-firm comparability. Empirically, the proposed metric offers a practical tool for benchmarking companies not only within the Polish construction sector but also across industries and countries, thus bridging a critical gap in applied financial management. We will begin our analysis with the development of this indicator. Accordingly, the article seeks to answer the following research questions:

1. Is it possible to develop a synthetic indicator to describe financing and working capital investment strategies?
2. Do companies in the construction sector in Poland apply differentiated working capital management strategies?
3. Does the chosen working capital management strategy significantly affect the profitability of the company?
4. Does the chosen working capital management strategy significantly affect the company's risk?

In addition, the analysis carried out will enable the verification of three research hypotheses:

H1: The construction sector is characterized by high homogeneity, resulting in companies pursuing similar financing and investment strategies.
H2: Aggressive working capital management strategies generate higher profitability than conservative strategies.
H3: Aggressive working capital management strategies are associated with higher risk than conservative strategies.

The proposed work not only fills a gap in the literature, but also provides practical guidance for managers and decision-makers in the construction sector, allowing them to better adapt working capital management strategies to the specific market conditions in Poland.

## 2. The methodology

Following the approach presented by Zabolotnyy and Sipilainen (2020), this study constructs two key indicators of working capital management strategies: $A_1$, corresponding to investment in working capital, and $A_2$, describing the financing of this capital. These indicators allow for a comprehensive analysis of the adopted strategies in relation to their aggressiveness or conservatism. Table 1 illustrates the set of variables with their abbreviations, formulas and assignment to the relevant indicators. An important observation is that the variety of variables captures both operational aspects, such as the efficiency of the use of current assets (e.g. CAT), and structural aspect (e.g. DE).

**Table 1.** Indicators of WCM strategies and their effect on the aggregate ratio

| Variable | Acronym | Equation | Group | Effect |
|---|---|---|---|---|
| $X_1$ | CAT | Sales/Avg. Current Assets | $A_1$ | Positive |
| $X_2$ | PPET | Sales/Avg. PP&E | $A_1$ | Negative |
| $X_3$ | θC | Avg. CCE/Avg. Total Assets | $A_1$ | Negative |
| $X_4$ | CAFA | Avg. Current Assets/Avg. Fixed Assets | $A_1$ | Negative |
| $X_5$ | CLT | Sales/Avg. Current Liabilities | $A_2$ | Negative |
| $X_6$ | θCL | Avg. Current Liabilities/Avg. Total Assets | $A_2$ | Positive |
| $X_7$ | DE | Avg. Liabilities/Avg. Equity | $A_2$ | Positive |
| $X_8$ | SDCE | Avg. Current Liabilities/Avg. Capital Engaged | $A_2$ | Positive |

Source: Own research based on: Zabolotnyy S., Sipiläinen T. (2020), A comparison of strategies for working capital management of listed food companies from Northern Europe, Agricultural and Food.

The variables described in Table 1 were used to construct the indicators, which are divided into groups according to their effect on each indicator. For variables whose growth promotes an aggressive strategy, their effect is positive, while for variables supporting a conservative strategy, their effect on the indicator is negative. For the following equations, indices n, c, and t denote the *n*-th variable, *c*-th company, and *t*-th period. In order to improve the quality of the aggregation and reduce the impact of potential outliers in the sample, the variables were normalized using the Z-Score. This process involves calculating the mean value and standard deviation for each variable in a given year, according to the formulas below:

$$\bar{X}_{nt} = \frac{1}{C}\sum_{c=1}^{C} x_{nct} \tag{1}$$

$$\sigma_{nt} = \sqrt{\frac{1}{C-1}\sum_{c=1}^{C}(x_{nct} - \bar{X}_{nt})^2} \tag{2}$$

The standardized ratios were calculated according to the formula:

$$z_{nct} = \frac{x_{nct} - \bar{X}_{nt}}{\sigma_{nt}} \tag{3}$$

The use of Z-Score normalization in studies of this type is crucial, as it allows variables of different scales and units to be compared, and the unification of variable values eliminates the impact of differences in their distributions, which is particularly important when analyzing a sample that may include companies with radically different financial and operational structures. An additional step was to use a hyperbolic tangent function to limit the values of the variables to the range [-1;1]:

$$\begin{cases} +\left(tgh\, z_{nct} = \dfrac{e^{z_{nct}} - e^{-z_{nct}}}{e^{z_{nct}} + e^{-z_{nct}}}\right) & for\ positive\ effect \\ -\left(tgh\, z_{nct} = \dfrac{e^{z_{nct}} - e^{-z_{nct}}}{e^{z_{nct}} + e^{-z_{nct}}}\right) & for\ negative\ effect \end{cases} \tag{4}$$

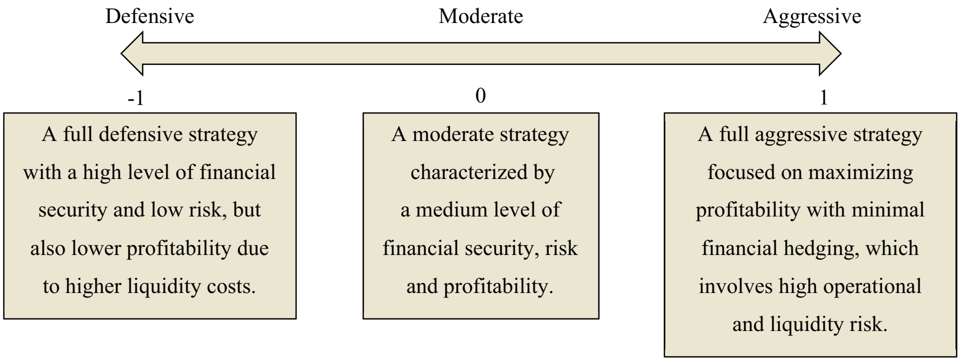
This procedure not only improves the interpretation of the results, but also prevents excessive outliers from affecting the aggregation of the indicators. This method can be considered optimal, as it amplifies differences in values close to the mean, giving more weight to differences in values close to zero, thus making the subtle differences between moderate strategies more visible, while suppressing the influence of extreme values, which, although still included, have a limited impact on the value of the final indicator, thus increasing its stability. Finally, the strategy indicators $A_1$ and $A_2$ were calculated as the arithmetic mean of the values of the variables assigned to the group:

$$A_{1ct} = \frac{1}{4}\sum_{n=1}^{4} tgh\, z_{nct} \tag{5}$$

$$A_{2ct} = \frac{1}{4}\sum_{n=5}^{8} tgh\, z_{nct} \tag{6}$$

Figure 1 shows a one-dimensional individual interpretation of the working capital management indicator, where negative values (-1 to 0) indicate a conservative strategy characterized by a greater emphasis on stability and financial security, positive values (0 to 1) represent an aggressive approach aimed at maximizing profits, and values close to 0 reflect a moderate strategy balancing risk and stability.

**Figure 1.** Interpretation of indicators A1 and A2

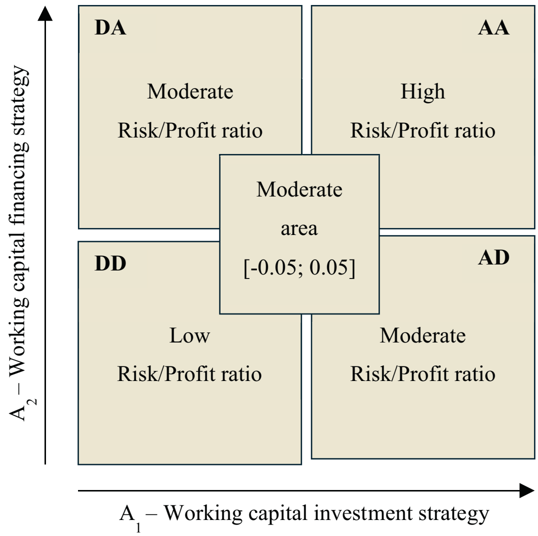



Source: Own research.

Figure 2 shows a two-dimensional interpretation of the working capital management strategy, where $A_1$ and $A_2$ are both visualized on the axes limited to the interval [-1;1]. The resulting matrix identifies four main strategic areas: DD (Defensive-Defensive) in the [$A_1$ < -0,05 and $A_2$ < -0,05] area characterized by risk minimization, DA (Defensive-Aggressive) in the [$A_1$ < -0,05 and $A_2$ > 0,05] area combining safe investments with risky financing, AD (Aggressive-Defensive) in the [$A_1$ > 0,05 and $A_2$ < -0,05] area indicating aggressive investments with conservative financing, and AA (Aggressive-Aggressive) in the [$A_1$ > 0,05 and $A_2$ > 0,05] area representing maximization of potential returns with high risk, with the space [-0.05; 0.05] for both indicators defines the area of moderate strategies.

To answer the research questions and test the hypotheses, a regression analysis was conducted. The impact of working capital management strategies on companies' profitability and risk was examined. Profitability indicators were operating margin, return on sales and return on equity, while risk was measured by the current liquidity ratio. The variables included in the regression models are detailed in Table 2, along with the corresponding formulas.

**Figure 2.** Characteristics of the Risk/Proft ratio with a working capital strategy




Source: Own research.

Formula (7) includes working capital management strategy indicators $A_1$ and $A_2$, a synergy variable ($\delta = A_1 * A_2$) which makes it possible to recognize whether there is an additional effect of adopting two of the same strategies and a counter-effect of adopting opposite ones. We also include company size (SIZE) and gross margin (GM) to capture the impact of scale of operations and cost efficiency.

$$OM = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 \delta + \beta_4 SIZE + \beta_5 GM + \varepsilon \quad (7)$$

$$ROS = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 \delta + \beta_4 GM + \beta_5 r_d + \varepsilon \quad (8)$$

$$ROE = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 \delta + \beta_4 GM + \beta_5 r_d + \beta_6 g + \varepsilon \quad (9)$$

**Table 2.** Descriptions and equations of the variables in the regression model

| Variable | Description | Equation |
|---|---|---|
| GM | Gross margin | 1 – COGS/Sales |
| OM | Operating margin | EBIT/Sales |
| ROS | Return on sales | Net Income/Sales |
| ROE | Return on equity | Net Income/Avg. Equity |
| CR | Current ratio | Avg. Current Assets/Avg. Current Liabilities |
| ICR | Interest coverage ratio | EBIT/Interest |
| δ | Synergy factor | $A_1 * A_2$ |
| SIZE | Company size | ln(Avg. Total Assets) |
| g | Sales growth | $Sales_t/Sales_{t-1} - 1$ |
| $r_d$ | Cost of debt | Interest/Avg. Debt |

Source: Own research.

Formula (8) additionally considers the cost of debt ($r_d$), examining how financing strategies interact with profitability of sales. Formula (9) extends the analysis to include sales growth rate (g), highlighting the importance of expansion in increasing ROE.

$$CR = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 \delta + \beta_4 SIZE + \beta_5 ICR + \varepsilon \tag{10}$$

Formula (10) relates to risk, as measured by the liquidity ratio (CR), and takes into account the interest coverage ratio (ICR), which indicates the firm's ability to service its interest obligations, highlighting the key impact of financial strategies on liquidity stability.

For the purpose of the analysis, 33 companies from the construction sector, listed on the Warsaw Stock Exchange and the NewConnect market, were selected, covering the period from 2019 to 2023. The sample was restricted to companies with positive equity only, excluding entities with negative equity to ensure consistency and reliability of the results. The data used in the study was obtained from the EMIS database, which provides detailed financial and operational information on companies.

## 3. Results

In response to the first research question concerning the possibility of developing a synthetic indicator describing financing and working capital investment strategies, the results of the research confirm that it has been possible to successfully create such a measure.

**Table 3.** Results of working capital management indicators

| | $A_1$ | | | | | $A_2$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Firm** | **2020** | **2021** | **2022** | **2023** | **Mean** | **2020** | **2021** | **2022** | **2023** | **Mean** |
| 1AT | -0.55 | -0.62 | -0.70 | -0.72 | -0.65 | -0.11 | -0.09 | -0.13 | -0.25 | -0.15 |
| ATR | 0.66 | 0.41 | 0.39 | 0.31 | 0.44 | 0.23 | 0.29 | 0.26 | 0.19 | 0.24 |
| BDX | -0.29 | -0.14 | -0.17 | -0.19 | -0.20 | 0.78 | 0.79 | 0.80 | 0.80 | 0.79 |
| DEK | -0.11 | 0.01 | -0.06 | -0.11 | -0.07 | 0.21 | 0.26 | 0.15 | -0.08 | 0.13 |
| DOM | -0.77 | -0.76 | -0.68 | -0.56 | -0.69 | 0.15 | 0.31 | 0.40 | 0.34 | 0.30 |
| ELT | 0.36 | 0.38 | -0.26 | -0.21 | 0.07 | -0.05 | -0.01 | -0.01 | 0.04 | -0.01 |
| ENI | 0.51 | 0.59 | 0.73 | 0.60 | 0.61 | -0.60 | -0.34 | -0.08 | 0.00 | -0.26 |
| ENP | 0.44 | -0.08 | 0.06 | -0.18 | 0.06 | -0.58 | -0.73 | -0.75 | -0.60 | -0.66 |
| ERB | -0.06 | -0.11 | 0.12 | 0.37 | 0.08 | 0.28 | 0.08 | -0.04 | 0.08 | 0.10 |
| HMI | 0.06 | 0.01 | -0.07 | -0.33 | -0.08 | 0.64 | 0.43 | 0.70 | 0.28 | 0.51 |

**Table 3** (cd.)

| Firm | $A_1$ | | | | | $A_2$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2020 | 2021 | 2022 | 2023 | Mean | 2020 | 2021 | 2022 | 2023 | Mean |
| HRS | 0.41 | 0.44 | 0.53 | 0.70 | 0.52 | -0.28 | -0.19 | -0.14 | 0.00 | -0.15 |
| INK | 0.08 | 0.12 | 0.22 | 0.18 | 0.15 | -0.74 | -0.74 | -0.76 | -0.62 | -0.72 |
| INP | -0.10 | -0.03 | 0.02 | 0.08 | -0.01 | -0.26 | -0.29 | -0.42 | -0.41 | -0.34 |
| MCR | 0.60 | 0.58 | 0.58 | 0.67 | 0.61 | -0.67 | -0.63 | -0.68 | -0.73 | -0.68 |
| MDI | -0.72 | -0.35 | -0.20 | -0.09 | -0.34 | 0.37 | 0.58 | 0.70 | 0.70 | 0.59 |
| MRB | 0.04 | -0.12 | 0.01 | 0.22 | 0.04 | -0.48 | -0.43 | -0.33 | -0.30 | -0.38 |
| MSP | 0.36 | -0.15 | 0.16 | 0.36 | 0.18 | 0.43 | 0.42 | -0.07 | -0.03 | 0.19 |
| MSW | -0.47 | -0.23 | -0.22 | -0.02 | -0.24 | 0.90 | 0.90 | 0.84 | 0.84 | 0.87 |
| NVA | 0.53 | 0.26 | 0.24 | 0.24 | 0.32 | -0.33 | -0.41 | -0.34 | -0.39 | -0.37 |
| PBX | 0.28 | 0.39 | 0.49 | 0.41 | 0.39 | -0.43 | -0.22 | 0.01 | 0.12 | -0.13 |
| PJP | 0.46 | 0.61 | 0.29 | 0.49 | 0.46 | -0.43 | -0.03 | -0.07 | 0.01 | -0.13 |
| PRM | 0.14 | 0.42 | 0.26 | 0.20 | 0.26 | -0.46 | -0.22 | -0.26 | -0.58 | -0.38 |
| PXM | 0.04 | -0.14 | -0.15 | 0.19 | -0.01 | -0.06 | 0.07 | 0.02 | 0.13 | 0.04 |
| QRT | -0.29 | -0.09 | 0.01 | -0.07 | -0.11 | -0.29 | -0.89 | -0.91 | -0.91 | -0.75 |
| RMK | -0.07 | -0.13 | -0.05 | 0.02 | -0.06 | 0.67 | 0.62 | 0.15 | 0.02 | 0.37 |
| STX | -0.24 | -0.22 | -0.12 | -0.23 | -0.20 | -0.41 | -0.46 | -0.43 | -0.36 | -0.42 |
| TME | 0.24 | 0.45 | 0.57 | 0.50 | 0.44 | -0.37 | -0.50 | -0.60 | -0.13 | -0.40 |
| TOR | -0.18 | 0.00 | -0.14 | -0.24 | -0.14 | 0.68 | 0.54 | 0.24 | -0.02 | 0.36 |
| TOS | 0.22 | 0.24 | -0.01 | -0.13 | 0.08 | -0.31 | -0.23 | -0.30 | -0.37 | -0.30 |
| TRK | 0.34 | 0.39 | 0.41 | 0.18 | 0.33 | 0.31 | 0.37 | 0.78 | 0.86 | 0.58 |
| TSG | 0.66 | 0.44 | 0.42 | 0.37 | 0.47 | -0.77 | -0.65 | -0.65 | -0.78 | -0.71 |
| UNI | 0.00 | 0.06 | 0.04 | 0.12 | 0.06 | 0.14 | 0.41 | 0.59 | 0.71 | 0.46 |
| ZUE | 0.53 | 0.46 | 0.33 | -0.04 | 0.32 | 0.19 | 0.37 | 0.53 | 0.51 | 0.40 |

Source: Own research.

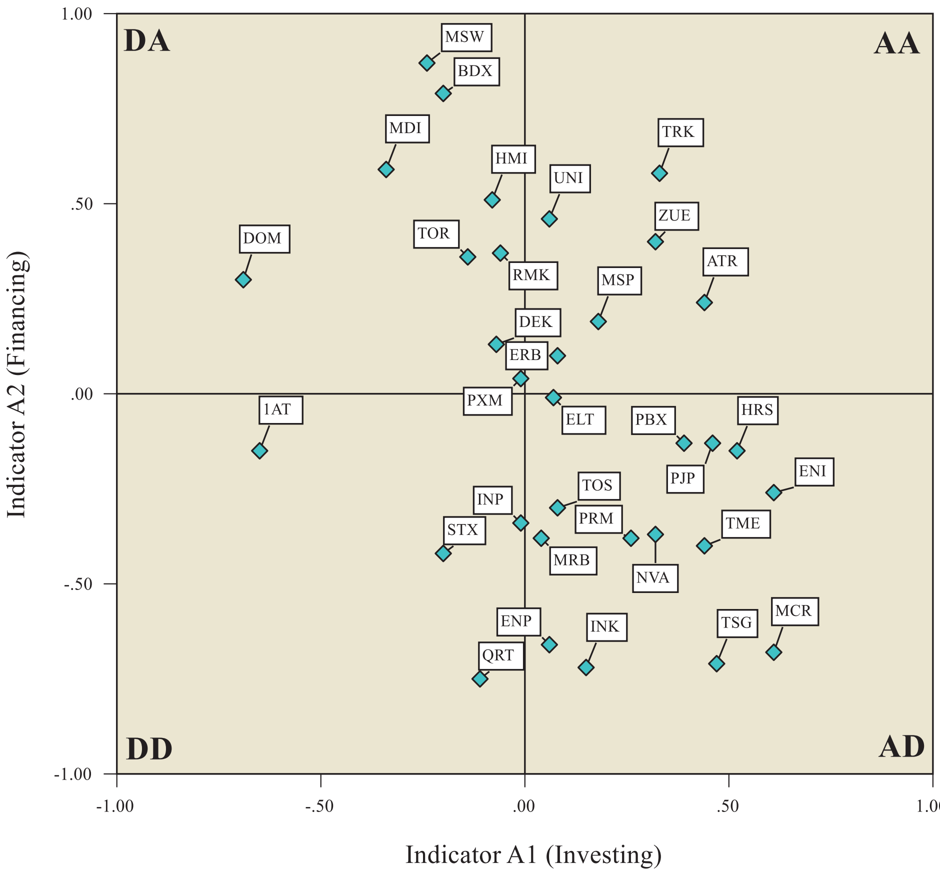
The developed $A_1$ and $A_2$ indicators show an equilibrium character, which means that their interpretation is strictly dependent on the context of the analysis – both with regard to the research sample and the reference point. The values of the indicators are consistent with the strategic assumptions made and reflect the specifics of working capital management in the companies analyzed. Importantly, this indicator can serve as a flexible analytical tool, allowing comparisons both within a single sector and between different industries.

**Table 4.** Strategies pursued by companies

| Investing | | | Financing | | | Combination | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D | M | A | D | M | A | DD | DM | DA | MD | MM | MA | AD | AM | AA |
| 11 | 3 | 19 | 17 | 2 | 14 | 3 | 0 | 8 | 2 | 1 | 0 | 12 | 1 | 6 |

Source: Own research.

**Figure 3.** Working capital management strategies in the construction sector




Source: Own research.

Analyzing the second research question relating to the diversity of working capital management strategies in the Polish construction sector, the empirical data indicates a significant diversity of approaches adopted. The analysis of the data in the Table 3 and 4 shows that companies use different combinations of strategies, with the most common ones being an aggressive strategy in investing combined with a defensive strategy in financing (AD) – used by 12 companies, and a defensive strategy in investing with an aggressive strategy in financing (DA) – found in eight cases. Less popular is the combination of two aggressive strategies (AA), which was identified in six entities. With regard to hypothesis H1, assuming homogeneity of the construction sector in terms of the financing and investment strategies pursued, it was rejected. The analysis of the empirical data presented in the table clearly shows the existence of diverse combinations of strategies. Particularly evident is the tendency to avoid using identical strategies in the area of financing and investment, which may reflect a conscious effort to nullify synergies. The values of indicators $A_1$ and $A_2$ for individual companies (3) confirm the lack of a uniform approach to working capital management in the sector studied. Based on the descriptive statistics presented in Table 5, it can be seen that the companies studied are characterized by a moderate level of profitability, with an average ROE of 8.2% and an average operating margin of 6.6%. At the same time, significant variation is observed in terms of the working capital management strategies used, confirming the earlier conclusions about the heterogeneity of the sector in this respect.

**Table 5.** Descriptive statistics for the variables used in the empirical analysis

| Variable | Mean | SE | Median | σ | Min | Max |
|---|---|---|---|---|---|---|
| 1. Working capital management strategies indicators | | | | | | |
| 1a. A1 | 0.094 | 0.030 | 0.062 | 0.348 | -0.768 | 0.727 |
| 1b. A2 | -0.030 | 0.042 | -0.044 | 0.478 | -0.913 | 0.904 |
| 1c. δ | -0.054 | 0.012 | -0.017 | 0.141 | -0.506 | 0.317 |
| 2. Profitability and risk indicators | | | | | | |
| 2a. GM | 0.138 | 0.012 | 0.129 | 0.143 | -0.428 | 0.668 |
| 2b. OM | 0.066 | 0.009 | 0.060 | 0.103 | -0.354 | 0.348 |
| 2c. ROS | 0.035 | 0.010 | 0.040 | 0.113 | -0.565 | 0.317 |
| 2d. ROE | 0.082 | 0.022 | 0.112 | 0.252 | -1.289 | 0.572 |
| 2e. CR | 1.921 | 0.204 | 1.426 | 2.348 | 0.604 | 20.059 |
| 3. Control indicators | | | | | | |
| 3a. SIZE | 12.917 | 0.138 | 13.008 | 1.583 | 8.347 | 15.883 |
| 3b. g | 0.114 | 0.030 | 0.067 | 0.340 | -0.602 | 1.757 |
| 3c. rd | 0.078 | 0.007 | 0.061 | 0.082 | -0.041 | 0.662 |

Source: Own research.

Referencing to the third research question concerning the impact of working capital management strategies on company profitability, the empirical research conducted provides clear evidence of a significant relationship. The analysis of the three regression models (M1, M2, M3) showed that the selected working capital management strategies have a mostly equal impact on the different measures of company profitability. The M1 model, explaining the variation in OM, has a very high level fit and is statistically significant. The results indicate that both the investment strategy ($A_1$) and the financing strategy ($A_2$) have a negative impact on the operating margin, with the impact of the investment strategy being significantly stronger (coefficient -0.069) than that of the financing strategy (-0.022). It is worth noting that GM proved to be the strongest predictor of operating margin with a positive coefficient of 0.548.

Similar relationships were observed in model M2, which analyses the impact of strategies on ROS. The model also has a high level of fit and confirms the negative impact of aggressive strategies, with a stronger impact of investment strategies (coefficient -0.084) compared to financing strategies (-0.025).

**Table 6.** Regression result of profitability prediction models

| | Model 1 | | | Model 2 | | | Model 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| VAR | Coeff. | t | p | Coeff. | t | p | Coeff. | t | p |
| C | -0.059 | -1.597 | 0.113 | 0.010 | 1.109 | 0.270 | 0.001 | 0.020 | 0.984 |
| A1 | -0.069** | -5.469 | 0.000 | -0.084** | -5.692 | 0.000 | -0.116* | -2.005 | 0.047 |
| A2 | -0.022* | -2.179 | 0.031 | -0.025* | -2.385 | 0.019 | 0.081* | 1.984 | 0.049 |
| δ | 0.022 | 0.792 | 0.430 | 0.026 | 0.815 | 0.416 | -0.377** | -3.067 | 0.003 |
| SIZE | 0.004 | 1.474 | 0.143 | | | | | | |
| GM | 0.548** | 16.870 | 0.000 | 0.503** | 14.241 | 0.000 | 0.723** | 5.356 | 0.000 |
| rd | | | | -0.451** | -8.217 | 0.000 | -0.579** | -2.759 | 0.007 |
| g | | | | | | | 0.172** | 3.341 | 0.001 |
| R2 | 0.833 | | | 0.811 | | | 0.452 | | |
| Adj. R2 | 0.826 | | | 0.804 | | | 0.425 | | |
| F-stat | 125.545 | | | 108.162 | | | 17.167 | | |
| D-W | 2.019 | | | 2.232 | | | 2.164 | | |
| M1 | $OM = -0{,}059 - 0{,}069A_1 - 0{,}022A_2 + 0{,}022\delta + 0{,}004SIZE + 0{,}548GM$ | | | | | | | | |
| M2 | $ROS = 0{,}010 - 0{,}084A_1 - 0{,}025A_2 + 0{,}026\delta + 0{,}503GM - 0{,}451r_d$ | | | | | | | | |
| M3 | $ROE = 0{,}001 - 0{,}116A_1 + 0{,}081A_2 - 0{,}377\delta + 0{,}723GM - 0{,}579r_d + 0{,}172g$ | | | | | | | | |

Note: ** p < 0,01; * p < 0,05.

Source: Own research.

The cost of debt also plays an important role in this model, showing a significant negative impact on return on sales (-0.451). The M3 model, focusing on ROE, presents slightly different results. With a lower but still satisfactory level of fit, the model shows an interesting dichotomy: while an aggressive investment strategy still has a negative impact (-0.116), an aggressive financing strategy has a positive impact on ROE (0.081). This positive relationship may be due to the leverage effect and the mechanical reduction of the ROE denominator. In light of the above results, hypothesis H2, which assumes that aggressive working capital management strategies generate higher profitability than conservative strategies, was rejected. The empirical data indicates that, in most cases, an aggressive approach to working capital management leads to lower profitability. The only exception is the positive effect of an aggressive financing strategy on ROE, which, however, may be more related to the mechanism of the indicator than to actual improvements in operational efficiency.

**Table 7.** Regression result of risk prediction model

| VAR | Model 4 | | |
|---|---|---|---|
| | **Coeff.** | **t** | **p** |
| C | 6.628** | 4.110 | 0.000 |
| A1 | -1.450* | -2.394 | 0.018 |
| A2 | -1.732** | -2.179 | 0.000 |
| δ | 2.481* | 1.984 | 0.049 |
| SIZE | -0.376** | -3.066 | 0.003 |
| ICR | 0.028** | 2.947 | 0.000 |
| R2 | | 0.334 | |
| Adj. R2 | | 0.308 | |
| F-stat | | 12.660 | |
| D-W | | 2.016 | |
| M4 | $CR = 6{,}628 - 1{,}45A_1 + 1{,}732A_2 + 2{,}481\delta - 0{,}376SIZE - 0{,}028ICR$ | | |

Note: ** p < 0,01; * p < 0,05.

Source: Own research.

Focusing on the fourth research question, concerning the impact of working capital management strategies on company risk, the empirical analysis conducted provides convincing evidence of a significant relationship. The M4 model, investigating the effect of strategy on the CR, shows a moderate fit and is statistically significant. The results indicate that both the aggressive investment strategy ($A_1$) and the funding strategy ($A_2$) have a significant negative impact on the current liquidity ratio, with coefficients of -1.450 and -1.732, respectively. A particularly interesting finding is the δ between strategies, which partially mitigates the increase in liquidity risk (coefficient 2.481). Referring to the regression results, hypothesis H3, which assumes that aggressive working capital management strategies are associated with higher risk than conservative strategies, is confirmed. The model also reveals the important role of control variables – company size shows a negative effect on the liquidity ratio (-0.376), suggesting that larger companies can afford a higher level of risk due to better access to external financing. At the same time, the ICR has a weak but positive impact on liquidity (0.028), indicating that companies with lower debt levels have lower liquidity risk. It is worth noting that the average current ratio in the sample is 1.921 (Table 5), indicating a relatively safe level of liquidity in the sector.

## Conclusions

The results of the study indicate an interesting divergence from the dominant strand of working capital management theory. While a significant body of literature, including studies by Singh et al. (2017), Nazir and Afza (2009) and Deloof (2003), indicates a positive relationship between aggressive strategies and profitability, our study found different results in the construction sector. We observed that an aggressive approach to working capital management negatively affects firms' profitability, while confirming the traditional assumption of higher risk associated with such strategies, which is supported by the work of Akbar et al. (2021), Wieczorek-Kosmala et al. (2016) and Al-Shubiri (2011). The results obtained can be explained by the peculiarities of the construction sector and the macroeconomic conditions of the research period. As demonstrated by Mielcarz et al. (2018), during periods of increased economic uncertainty, more profitable firms often adopt conservative working capital management strategies. This is particularly relevant in the context of the construction sector, where the implementation of projects requires significant financial outlays over a long period of time before there is a return in the form of revenues. Our findings correspond with studies by Zeidan and Vanzin (2019) and Ng et al. (2017), who observed that firms with longer cash conversion cycles often achieve higher operating margins, despite theoretically less efficient working capital management. High levels of uncertainty in the macro-environment, including supply chain disruptions and the economic downturn, have particularly affected the construction industry. Firms aggressively managing working capital may have been more vulnerable to liquidity problems, as evidenced in studies by Yang and Birge (2017) and Kieschnick et al. (2012). In this context, more conservative working capital management strategies, based on maintaining higher cash reserves and greater financial stability, were found to be more effective in protecting profitability, which is consistent with the findings of Maswadeh (2015) and Vishnani and Shah (2007). Our recommendations for business practice are based on several key findings. First, as observed by Zimon (2020) and Zabolotnyy and Wasilewski (2019), construction firms should adopt a more defensive approach to working capital management that increases liquidity and minimizes risk. Second, as suggested by Makori and Jagongo (2013) and

Raheman and Nasr (2007), firms should focus on optimizing individual working capital components, tailoring strategies to sector-specific and macroeconomic conditions. Finally, our study indicates that theories from academic textbooks are often one-size-fits-all and do not take into account the specificities of individual sectors, as confirmed by the work of Nuhiu and Dermaku (2017) and Talonpoika et al. (2016).

Moreover, the implications of our findings extend beyond the construction sector and are relevant to all industries characterized by long project realization cycles. In periods of heightened uncertainty or when there is a significant risk of payment bottlenecks in the economy, managers should strongly consider adopting more conservative policies regarding both financing and investment decisions. Our analysis shows that any potential gains from aggressive approaches are overwhelmingly offset by losses once a "black swan" event occurs. Construction halts, combined with difficulties in debt rollover, proved far more damaging than any short-term profitability improvements. Therefore, the strategic stance of firms operating in uncertainty-prone sectors should prioritize resilience and liquidity over theoretical efficiency gains. The study is limited to public construction firms in Poland and a specific economic period. Future research could test the robustness of these findings in other sectors or countries.

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# The Transformative Power of Generative AI in Financial Service: A Comprehensive Review

## Summary

In the current context, where digital technologies are ubiquitous in most human activities, digital transformation remains a key area of research with global effects. Among these technologies, generative AI (GenAI) is emerging as a particularly disruptive force. It is transforming industries by automating processes, improving decision-making and driving business innovation.

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The main objective of this paper is to review and synthesize the literature to define artificial generative intelligence and how it influences the financial services industry, presenting the positive and negative aspects of the use of this technology.

The paper comprises two major parts. The first part aims to define the GenAI technology, analyzing its essence and how it works, and the second part comprises a literature review on how artificial generative intelligence influences financial services, thus highlighting both the advantages, as well as the negative aspects of using the technology.

The research findings could be valuable to individuals who are unfamiliar with GenAI technology, or are interested in its impact on the business environment, in particular financial services.

**Keywords:** GenAI, financial services, automation, operational efficiency, AI ethics, data privacy

**JEL Classification:** G2, O1, O3, Q55

# Transformacyjna siła generatywnej sztucznej inteligencji w usługach finansowych: kompleksowy przegląd

## Streszczenie

W obecnych czasach, w których technologie cyfrowe są wszechobecne w większości ludzkich działań, transformacja cyfrowa pozostaje kluczowym obszarem badań o globalnym zasięgu. Wśród tych technologii, generatywna sztuczna inteligencja (GenAI) staje się szczególnie przełomową potęgą. Przekształca ona branże poprzez automatyzację procesów, usprawnianie procesu decyzyjnego i napędzanie innowacji biznesowych.

Głównym celem niniejszego artykułu jest przegląd i synteza literatury w celu zdefiniowania sztucznej inteligencji generatywnej i jej wpływu na branżę usług finansowych, przy jednoczesnym przedstawieniu pozytywnych i negatywnych aspektów wykorzystania tej technologii.

Artykuł składa się z dwóch głównych części. Pierwsza część ma na celu zdefiniowanie technologii GenAI, analizę jej istoty i sposobu działania, a druga część obejmuje przegląd literatury na temat wpływu sztucznej inteligencji generatywnej

na usługi finansowe, wskazując w ten sposób zarówno zalety, jak i negatywne aspekty korzystania z tej technologii.

Wyniki badań mogą być cenne dla osób, które nie są zaznajomione z technologią GenAI lub są zainteresowane jej wpływem na środowisko biznesowe, w szczególności usługi finansowe.

**Słowa kluczowe**: GenAI, usługi finansowe, automatyzacja, efektywność operacyjna, etyka AI, prywatność danych

## Introduction

In today's context, where digital technologies are ubiquitous in most human activities, digital transformation remains a prominent concept, while its essence, impact and implementation represent current research topics in academia. In essence, digital transformation is not only about integrating and using digital technologies, but also about reshaping and adapting business processes in order to fully exploit the potential of these technologies (Bodendorf and Franke, 2024; Khuntia et al., 2024; Leso et al., 2024).

One of the technologies that has strongly impacted society is artificial intelligence. It has advanced rapidly in recent years, reshaping industries and fundamentally changing business processes (Mungoli, 2023; Raju and Sumallika, 2023; Rakha, 2023). Among the different branches of AI, generative AI has emerged as a particularly disruptive force, driving significant changes in the way businesses operate, innovate and compete (Bilgram and Laarmann, 2023; Chen et al., 2023). The integration of advanced artificial intelligence technologies is not just a trend, but a transformative change virtually affecting all aspects of business, from internal operations to external market strategies.

The main objective of this paper is to review and synthesize the specialized literature in order to define artificial generative intelligence and how it impacts the financial services industry, presenting the positive and negative aspects of this technology usage in areas such as customer support service, personalized financial planning, fraud detection, risk management and credit scoring. Through compilation and consolidation, the various findings of the studies will define the transformative potential that generative artificial intelligence possesses, implying changes in business practices.

To conduct this analysis, the following secondary objectives were set:

1. defining the GenAI technology as well as its purpose;
2. exploring the usefulness of GenAI in specific financial services;
3. identifying the advantages and disadvantages of integrating GenAI in financial services.

The following hypotheses were also defined:

H.1. Generative AI contributes to improving operational efficiency, accuracy, and productivity in financial services, by automating processes, reducing manual tasks, and enhancing decision-making.

H.2. Generative AI could reduce the cost of financial service delivery by automating routine processes, improving customer service through chatbots, and optimizing resource allocation.

H.3. Generative AI could enhance personalized customer experience by providing tailored financial advice, automated portfolio management, and real-time insights, yet may pose risks related to data privacy, biases, and ethical concerns.

## Methodology

The proposed analysis has used a systematic approach as methodology, by analyzing specialized articles, reports from the industry, and case studies published within the last decade. When selecting sources, relevance and timeliness were considered key aspects, being prioritized to serve the research objectives and hypotheses.

Moreover, the research uses an integrative analytical framework that synthesizes findings from multiple sources to identify dominant trends, conceptual convergences across authors or institutions, and gaps in the current understanding of how generative AI is transforming the business environment. This approach supports the formulation of well-founded conclusions and provides a solid starting point for future research.

The process of ensuring the coherence and relevance of the information collected implied a preliminary evaluation of the materials included in the study, considering the quality of the content, the credibility of the authors or institutions and the degree to which they address concrete aspects related to the implementation and impact of generative AI in different business contexts. Regarding the quality of the content, the perspective of methodological rigor and the depth of the analysis provided by each source were taken into account. Thus, the papers that present thorough research, based on solid empirical and theoretical data, addressing in detail concepts, applications and concrete examples of the implementation of generative AI in different business areas were prioritized. Concerning the credibility of the authors and institutions, sources from recognized authors in the field and from prestigious organizations or institutions with expertise in AI technology were selected. The focus was on articles published in top academic journals and reports issued by institutions that are well-known for their high-quality standards of analysis. In addition, the relevance of the sources was assessed based on their topicality and applicability in the context of the rapid evolution of generative AI technologies and the way they influence economic activity. Thus, the selected sources reflected not only theoretical research, but also analyses from the professional environment, providing a complete and updated picture of the subject. Although this process did not follow a formalized protocol, it allowed the selection of sources that could significantly contribute to the understanding of the phenomenon from multiple perspectives, namely technological, strategic and ethical.

However, there are several important limitations related to the methodology used that need to be mentioned. First, the analysis was exclusively based on secondary sources, which means that the interpretations and conclusions drawn mostly depend on the quality and objectivity of existing analyzed materials. The lack of primary data (such as interviews, surveys, or direct observations) limits the ability to empirically validate certain claims or to capture the contextual nuances of the approached phenomenon.

On the other hand, the selection of sources, although guided by clear criteria of relevance and timeliness, can introduce a publication bias, i.e., articles and studies that highlight positive effects or successful applications tend to be published more frequently than those that reflect failures, difficulties, or negative effects. Thus, the results may reflect an optimistic, but possibly incomplete, picture of reality.

Also, given the rapid pace of technological evolution and innovation in the field of artificial intelligence, some conclusions drawn from recent literature may quickly become outdated.

Despite the identified limitations, the methodology employed provides a coherent framework for exploring the considered phenomenon and provides a valuable theoretical foundation for further studies, especially of an empirical nature.

## Overview of Generative Artificial Intelligence

As the name implies, generative AI is a component of AI technology, capable of generating new content, ideas or models using knowledge learned from training data (Cao et al., 2023; Zohuri, 2023). This differs from typical artificial intelligence, which analyzes and predicts outcomes. Generative AI offers completely new creations, which can be simple text, images, music and even complex data models (Epstein et al., 2023). The purpose of this chapter is to define generative AI technology and how it works.

## What is Generative Artificial Intelligence?

Generative AI systems are those that can generate new content, such as text, images, music or other forms of media, using knowledge from existing data (Cao et al., 2023; Zohuri, 2023). These systems are distinguished by their incredible ability to create results that are often indistinguishable from those created by a human. The nature of the design of such systems is that computers create things on their own by identifying structures and patterns in the data set with which they are trained (Gm et al., 2020). Therefore, this means that the basic idea behind generative AI is to create evolutions that would be different from those obtained in the input dataset, but rather new, unique and meaningful.

Compared to the dawn of AI research, the concept of generative AI has shifted significantly over time. Initial explorations were rule-based conversational chatbots, several of which were developed during the 1970s: *ELIZA*, *SCHOLAR*, and *MYCIN*, among many others (Gupta et al., 2024). These employed patterns matching with outcomes from pre-scripted responses and lacked the capability to generate new content or deeply understand conversational contexts, which are prevalent in modern GenAI systems.

Nowadays, generative artificial intelligence encompasses a range of methodologies and technologies designed to enable the creation of different content (Gm et al., 2020; Zohuri, 2023). Each type of generative artificial intelligence has a particular form of output that it creates, and such technologies have found application in many domains, affecting the way businesses and people create and interact with content (Bandi et al., 2023; Hofmann et al., 2021).

Perhaps the best-known form of GenAI is text generation. This involves fitting large language models to vast datasets of books, websites, social media posts and all other forms of written content (Epstein et al., 2023; Koga, 2023). These models, such as *OpenAI's GPT* series, can generate text that is considered to be very similar to human-written text. They can write essays, articles, poems, and even engage in conversations. As a result, they are applied in content creation, customer service, and automated writing assistance.

Apart from texts, GenAI is able to generate images. This form of AI depends on models that have been trained on huge collections of visual material, which enables it to build ultra-realistic pictures or even artistic images (Bermano et al., 2022; Jain and Thareja, 2019). Using different tools like *DALL-E* and *StyleGAN*, one can generate images either from text descriptions or completely new visuals synthesized from fragments of existing images. These capabilities have immense consequences for industries reliant on visual content: advertising, fashion, and design.

Another important type of generative AI is used to create music and audio. These systems create completely new music using models previously trained on very large databases of music (Kamath et al., 2024; Onuh Matthew Ijiga et al., 2024). Thus, by observing the patterns in the data, such as rhythm, melody, and harmony, one can use that to create new compositions applicable in a wide range of different uses, such as entertainment, media production, and personal soundtracks.

Video creation is one of the most emerging sectors in the field of generative AI, which generally involves creation or enhancement of content in video formats (Divya and Mirza, 2024; Zhou et al., 2024). This could be really useful in cinematography industries, virtual reality, and video game development (Aldausari et al., 2020; Zhang et al., 2024). Such AI systems, which are trained on large datasets comprising video clips, can form new sequences, animate characters, or even entire scenes, saving time and money in video production.

Generative AI has also applicability in data and code generation. For example, in most scenarios where either the real world has little data or the data is sensitive, synthetic datasets are always generated for training other AI models (Ebert and Louridas, 2023; Sun et al., 2022). Similarly, AI-powered developer tools like *GitHub's Copilot* generate code snippets, or give suggestions to improve existing code and, therefore, making software development seamless.

Each of these generative AIs specializes in the generation of different types of content, but they have one thing in common: *the ability to produce indistinguishable outputs from humans* (Cao et al., 2023; Gm et al., 2020; Zohuri, 2023). These new developments have allowed the industry to provide faster content production, better creativity, and changed the way business is conducted.

## Understanding How Generative AI Operates

Generative AI works by means of complex computational models, which are supposed to learn patterns from huge datasets and later generate new content based on the learned knowledge (Cao et al., 2023; Feuerriegel et al., 2024; Zohuri, 2023). The process of how GenAI produces new content could best be understood with an examination of the underlying mechanics that comprise machine learning, neural networks, and specific algorithms tailored for content creation. This chapter will cover the main components and processes involved in making GenAI work.

## Machine Learning Foundations

At the heart of GenAI is machine learning (*ML*), a sub-domain of artificial intelligence in which computers are given the capabilities to learn from data without explicit programming (Feuerriegel et al., 2024; Lopez-Jimenez et al., 2020; Strobelt et al., 2021). In general, ML algorithms are trained on huge datasets so that these models learn patterns, make predictions, and generate new results (Ogunpola et al., 2024; Wang et al., 2020). In the context of generative AI, such learning basically involves supervised, semi-supervised or unsupervised learning, depending on the availability or unavailability of labelled data.

*Supervised learning* involves training a model on a labelled dataset, where each input is tagged with its correct output (Kalota, 2024). Thus, this model will learn how to map inputs to outputs and, therefore, will be able to produce similar outputs when new inputs are fed into the model. Using the same example for text generation, it may be trained on sentence-level labelled data, whereby a model can predict a word, group of words, or subsequent sentence of the given input.

In *unsupervised learning*, the model learns directly from the input data without any explicit labeling (Kalota, 2024). In contrast to the well-defined relationship between inputs and outputs, unsupervised learning models generally discover some hidden patterns or structures in the data. This could be for common applications such as clustering, where the model systematically groups similar data points into groups, or dimensionality reduction, where the model simplifies complicated data into understandable representations.

### Neural Networks and Deep Learning

The whole concept of generative AI focuses on neural networks, especially those from deep learning models with several layers in an interconnected node or neuron (Alwahedi et al., 2024; Cronin, 2024; Shelf, 2024). Each would take the input data and attempt to show increasingly abstract features, passing on this information to the next layer. In this hierarchical manner, the model learns complicated patterns and their relations in data.

The deep learning models in GenAI are constructed by employing various architectures like convolutional neural network (CNN), recurrent neural network (RNN), and transformers. CNNs can be used due to their strengths in spatial hierarchies related to visual data for purposes like image generation (Gupta et al., 2024; Hofmann et al., 2021; Kalota, 2024). RNNs are able to handle tasks where the data is sequential, like text and time series, simply because they store a memory of past inputs, which helps in generating coherent sequences.

Transformers represent one of the most radical developments in neural network architecture within NLP (Natural Language Processing) (Chitty-Venkata et al., 2022; Kalota, 2024). While RNNs process data sequentially, transformers can process an entire sequence of data context all at once, therefore much more effectively capturing long-range dependencies (Tiezzi et al., 2024). It is this trait that has made them so powerful in such applications as text generation, whose context extends over much of the text.

### Training and Fine-Tuning

Training a generative model involves it iteratively learning the underlying and hidden pattern of a large data set (Feuerriegel et al., 2024; Kalota, 2024). During training, the model parameters are optimized so that the generated output is very close to the real data (Gupta et al., 2024). Normally, these operations are computationally intensive and time-consuming.

Once trained, models can be adjusted to fit certain tasks or domains. This involves further training the model on a smaller, more specialized dataset, allowing it to hone its knowledge of the finer nuances in the new data (Cui et al., 2018). For example, general language could be fine-tuned on a corpus of legal texts to improve the output of documents on such topics.

## Generative Algorithms

Generative AI models use a variety of algorithms, each depending on the type of content they need to create (Cao et al., 2023; Gupta et al., 2024). Some of the common algorithms used for this purpose include:

- Generative Adversarial Networks (GAN): It falls into a class of algorithms that consists of two neural networks: one for generation and one for discrimination (Chakraborty et al., 2024; Gupta et al., 2024; Kalota, 2024). The work of creation is handled by a generator, which continuously produces new content and pits it against real data through a discriminator to continue the adversarial process, which steadily improves its capability of producing realistic content with time. GANs find a great amount of their application in image generation and have really been at the heart of high-quality synthetic images.
- Variational Autoencoders (VAE): VAEs also falls into the category of generative models. The goal of this model is to learn underlying distributions of the data, to then sample from this distribution and generate new content (Gupta et al., 2024; Kiran Mayee Adavala, 2024). They find their most useful applications in tasks related to creating variations of existing data, such as generating new models based on existing ones.
- Transformers: As mentioned before, transformers really proved to be very powerful for text and sequence-related tasks (Chitty-Venkata et al., 2022; Kalota, 2024). Indeed, they make use of a mechanism called self-attention, whereby the model gives more or less weight to different parts of the input data. This proves important for coherent generation to come out with contextually relevant text, hence the reason why transformers form the basis for a large number of modern language models (Gupta et al., 2024; Kalota, 2024).

## Output Generation

Training enables the generative AI model to create new content by sampling from that learned data distribution (Cao et al., 2023; Zohuri, 2023). Indeed, the process of generation may vary with different model types and tasks involved. In text generation, for example, it may receive a prompt or be asked to complete based on the trend it has learned (Gm et al., 2020). In image generation, this may also involve creating new images by mixing features of the different categories present in its training data.

The quality of generated output depends on several factors: the size and diversity of the training data, the model complexity, and, more importantly, concrete algorithms applied (Chakraborty et al., 2024; Feuerriegel et al., 2024; Gm et al., 2020). The most advanced generative models already generate content that is indistinguishable from those created by humans, hence making them extremely powerful in various applications.

## Summarizing Remarks on the Generative AI Mechanisms

The main purpose of this chapter was to define generative artificial intelligence, exploring its key concepts, methodologies and applications. GenAI is a powerful branch of artificial intelligence distinguished by its ability to create novel content, such as text, images, music, video, and data models, based on patterns learned from large datasets. Unlike traditional artificial intelligence systems that primarily analyze and predict, GenAI goes beyond these functions by generating completely new results, mimicking human creativity and innovation.

Chapter 2 also gave insight into the basic principles of GenAI: machine learning algorithms and neural networks lie at the heart of its operation. A lesson from vast datasets allows models to generate content in most cases, barely distinguishable from human-created outputs. That had enabled GenAI to span across a wide array of fields, starting with content creation and ending with customer service, financial services, and data generation.

For instance, models developed by OpenAI, such as those in the GPT series, have already demonstrated how this class of AI can almost achieve parity with human-generated text in applications that range from automated writing assistants and customer support to content creation. Beyond text, image creation utilities like DALL-E and StyleGAN show the power of GenAI in ultra-realistic or imaginative visuals that will change industries such as fashion, design, and advertising forever.

Further, the practical applications in domains such as music, video, and data generation were discussed. AI music and audio generation have opened up new vistas concerning entertainment and media production. Conversely, AI-driven video creation is rewriting the rules in the making of video content for cinematography and gaming. Subsequently, it went on to show how GenAI could provide synthesized data whenever such real data is unavailable or sensitive, hence earning its place as a key tool in the training of other models in the most varied situations.

It brings with it a host of challenges and limitations, foremost among them ethical concerns in the use of AI in content creation, especially regarding intellectual property, misinformation, and bias. As the models of GenAI continue to evolve, there is a growing prospect that such applications will end up producing devious content or amplifying seriously harmful biases embedded within the training data. The functionality of some GenAI models lacks transparency, which in turn again affects the comprehension or control of model output.

## The Usefulness of Generative AI in Streamlining Financial Services

Generative artificial intelligence is increasingly recognized as a powerful tool for transformation in various industries, including financial services (Cronin, 2024; Singh and Ahuja, 2024). By automating processes, improving decision-making and providing personalized services, GenAI can streamline many aspects of financial service delivery. This technology can be applied in areas such as customer service, fraud detection, credit scoring and portfolio management, delivering increased efficiency and accuracy.

Financial institutions are under constant pressure to reduce operational costs, improve customer experience and maintain regulatory compliance (Marco Iginio Bonelli and Esra Döngül, 2023). GenAI helps address these challenges by generating customized solutions, either by automating investment strategies or enhancing risk management systems (Cronin, 2024). GenAI's potential to reshape the industry lies in its ability to manage vast amounts of data, learn from models, and provide real-time insights, making financial operations faster, more efficient, and more customer centric.

However, besides benefits, many challenges and downsides are also associated with integrating GenAI into financial services, like lost human touch in customer service, defective decision-making, privacy risks, and reliance on automation (Chi and Hoang Vu, 2023; Montemayor et al., 2022; Zhang et al., 2022).

This chapter reviews literature to find out not only the applications and benefits of GenAI in streamlining financial services but also its drawbacks, to provide a balanced analysis of its overall effect on the industry.

### Customer Support Service Automation

Generative AI became an important tool for automating customer support services in many industries, and it did so in the financial services field. It makes operations smoother, responds quicker, and experiences personalized, and therefore improves the customer experience (Brynjolfsson et al., 2023; Xu et al., 2020).

Traditional methods of customer support can be slow and repetitive, leading to frustration for customers, and chatbots with GenAI can streamline support, making it faster, more accurate and much more personalized (Dihingia et al., 2021; N S, 2023). Anything from simple inquiries into account information to advisory roles on financial matters can fall under the job description these chatbots do. They operate around the clock, and there is no queue for support agents. Other than that, GenAI chatbots can understand natural language-meaningful expressions, which will make the interaction friendlier and even more conversational for the users.

More than just questions, generative AI may also offer customized advice in finance once it considers customer data such as spending patterns, income, and financial objectives. The more personalized, the more customers are satisfied and confident (Amutha, 2023; Hentzen et al., 2022). As if speaking to the most prominent benefits of GenAI in automating customer service, it can engage thousands of queries at a time while human agents can only handle one conversation at any given time (Xu et al., 2020). This further cut waiting periods and operational costs because human agents are freed from doing routine tasks.

Moreover, multilingual support shall enable customers from various parts of the world to communicate with financial institutions in native dialects (Feuerriegel et al., 2024). Other tasks, such as password reset, update on transaction status, and account information, can also be automated, thus freeing the human agents to deal with more complex issues. In case the AI is unable to solve a customer's problem, it routes the inquiry to a human agent, hence making the transition smoother by collecting relevant information before routing.

### Downsides of GenAI in Customer Support Service Automation

On the other hand, the use of GenAI in customer service has disadvantages. The main inconvenience refers to a serious lack of human empathy, necessary when situations such as disputes or emotional inquiries about finances arise (Chi and Hoang Vu, 2023; Montemayor et al., 2022). Though responses through generative AI are quick and relevant, it cannot match the personal touch of such situations, which creates dissatisfaction among customers. Besides, complex and ambiguous queries by GenAI can result in wrong responses that irritate customers.

There is also the risk of financial institutions over-reducing their customer service teams on the grounds that AI will handle most of the queries. This may lead to delays in resolving complicated or sensitive issues that demand human judgment.

A larger concern is data privacy and security. Given that much of the customer data is required to be accessed by the generative artificial intelligence models for personalized assistance, there is a high potential for data breaches or unauthorized disclosure (Ibrahim Arpaci, 2023). It is important to make the system transparent to customers by taking rigorous security measures to build trust in AI-powered customer service systems so that customers do not have to worry about the security of their sensitive financial information.

## Personalized Financial Planning and Portfolio Optimization

Considering the main purpose of generative AI – i.e., creating content based on large volumes of data – could be considered an ideal technology that provides personalized experiences. From this perspective, the solution irreversibly changes the face of financial services in terms of personalized financial planning to portfolio optimization.

By analyzing huge volumes of data, GenAI provides personalized advice and strategies relevant to each person's financial needs, making financial planning more available and efficient (Singh and Ahuja, 2024).

In personalized financial planning, generative artificial intelligence automates the traditional manual process of a financial advisor who typically assesses a client's situation, goals and risk tolerance (Marco Iginio Bonelli and Esra Döngül, 2023; Sahare, 2023). Generative AI automates these assessments in real time to provide personalized financial advice and allows chatbots and AI-powered voice assistants to tell, based on a person's spending habits, income, and financial goals, how much they should save or invest or what kind of debt they should cut down on. This dynamic adaptation within changed market conditions or circumstances of a person makes sure that the advice which a person gets is up to date, thus enabling them to make better decisions.

In portfolio optimization, GenAI reaches an advanced decision-making level based on huge historical market data, financial reports, and economic indicators that point out a trend or pattern influencing the investment performance (Hentzen et al., 2022; Marco Iginio Bonelli and Esra Döngül, 2023). While continually learning from this data, generative AI predicts future market changes and recommends adjustments to maximize returns while controlling risk. This considers each investor's special financial goals, risk tolerance, and time horizon in generating customized investment strategies.

Also, generative artificial intelligence allows dynamic portfolio management by real-time updates in the strategies according to prevailing market conditions (Hentzen et al., 2022; Marco Iginio Bonelli and Esra Döngül, 2023; Sahare, 2023). For example, in instances of severe changes to the markets, such as abrupt stock price drops or interest rate changes, artificial intelligence may suggest changes to the portfolio or make them autonomously to protect from losses or seize new opportunities.

Furthermore, GenAI can simulate various economic scenarios, exposing portfolios to a range of risks, such as recession or market crash, to help investors make strategic decisions about asset allocation and risk management (Addy et al., 2024; Marco Iginio Bonelli and Esra Döngül, 2023). Automation by GenAI involves rebalancing the portfolio to ensure the portfolio stays on target without active investor intervention.

## Downsides of GenAI in Personalized Financial Planning and Portfolio Optimization

Also, as with the use of generative AI in the delivery of customer support services, the use of technology in personalized financial planning and portfolio optimization has several recognized downsides. A major concern is that there is a great risk of receiving incorrect or inappropriate financial advice. Indeed, GenAI's potential to perform well is closely linked to the quality of the data with which the model has been trained (Cronin, 2024; Feuerriegel et al., 2024). This data might be outdated, biased or incomplete, and it is therefore possible that the AI could make recommendations that are not in the user's best interest, thus leading to sub-optimal investment choices or financial strategies that are not in fact in line with real needs and goals (Hentzen et al., 2022).

Another concern about artificial intelligence is the absence of human intuition and an understanding of feelings in terms of the advice that can be offered (Chi and Hoang Vu, 2023; Montemayor et al., 2022). The personal nature of planning can really relate to life goals, family issues and even emotional comfort with risk. Although GenAI can provide logically correct suggestions, it is devoid of feelings or human understanding and empathy, which may make users distrust AI recommendations.

There is also the possibility of over dependence on AI to the detriment of individual financial literacy (Qirui Ju, 2023; Zhai et al., 2024). A user will tend to have an over reliance on recommendations made through AI without appreciating the financial principles governing such recommendations. This hampers the development of necessary skills for self-sufficient decision-making by the individual on financial matters. For example, where AI cannot help or fails to adapt to changes in personal circumstances, individuals may not be able to manage their finances effectively.

Also, for most people GenAI models are *"black boxes"*, users not being able to understand how it works, the fact that highlights a limited transparency in the decision-making process through which AI provides recommendations (Grange et al., 2024; Huang et al., 2024). This opacity could prevent investors from perceiving some of the risks that their investment strategy presents and mislead them into taking risks that are not aligned with their risk tolerance or long-term financial goals.

Then there are further issues of data quality and bias (Jain and Menon, 2023). If the data upon which the generative artificial intelligence models are trained is biased, partial, or stale, the recommendations made by the AI are potentially flawed or biased, which negatively impacts the financial outcome. Ensuring high-quality unbiased data is important but sometimes quite difficult to realize.

Ultimately, there are security and privacy concerns because of the sensitive financial information that these GenAI systems require (Singh and Ahlawat, 2023; Zhang et al., 2022). If these systems are not well secured, there is the potential for data breaches or unauthorized access that could affect personal and financial information. Such security vulnerabilities are likely to erode confidence in AI-enabled financial solutions and discourage users from adopting such technologies.

## Algorithmic Trading

Generative AI takes it to the next level by making trading strategies more effective and complex (Koshiyama et al., 2020; Singh and Ahuja, 2024). In algorithmic trading, computer programs automatically execute a trade following specific rules and predefined market data (Boming Huang et al., 2018). On this, GenAI does the work of creating completely new, self-learning trading algorithms out of big sets of historical data (Koshiyama et al., 2020). It will be able to help financial institutions and investors make better, thus more profitable, trading decisions.

Another way generative artificial intelligence enhances algorithmic trading is by analyzing huge volumes of data at unparalleled speeds (Feuerriegel et al., 2024; Koshiyama et al., 2020). Taking in substantial volumes of historical market data, a GenAI model can identify very complex patterns and develop insights driving trading decisions using that information (Kalota, 2024). That will continue to empower traders to develop algorithms that consider even more sophisticated conditions in the financial markets, such as price, trading volume, and market sentiment. These AI-powered strategies are much more precise and reliable than their predecessors, which rely on simpler rules or human intuition.

Generative artificial intelligence is also able to streamline high-frequency trading, another form of algorithmic trading that executes enormous numbers of orders at super-high speeds (Koshiyama et al., 2020; Viktor Manahov and Hanxiong Zhang, 2019). With the use of artificial intelligence, huge amounts of real-time data are analyzed and predictions about short-run market developments are made while proposing trades in milliseconds. Such a real-time response to fluctuation within the market does provide enormous competitive advantages, most especially in the fast financial markets.

Besides the predefined rules of trading, GenAI can constantly learn from incoming market data and change its strategies with it (Feuerriegel et al., 2024; Koshiyama et al., 2020; Singh and Ahuja, 2024). Such adaptiveness keeps the trading algorithms effective even during changes in market conditions.

The other important use of generative AI in algorithmic trading is strategy generation and optimization (Koshiyama et al., 2020; Marco Iginio Bonelli and Esra Döngül, 2023). GenAI will be able to simulate different trading scenarios to assist traders in testing the effectiveness of strategies under disparate market conditions before using them in live trading (Singh and Ahuja, 2024).

By design, the GenAI models can embed even risk management into trading algorithms. Generating risk-adjusted strategies, artificial intelligence has the potential to support traders in times of highly volatile market periods and help them reduce losses to a minimum (Kavin Karthik V, 2023; Koshiyama et al., 2020). That will be worth more, especially for those institutions and investors who have to balance their pursuit of profits with risk management. An AI-driven trading system can change the size of positions, place stop-loss orders, or hedge against unfavorable price movements by doing real-time market analysis.

## Downsides of GenAI in Algorithmic Trading Automation

Although it might seem at first glance that in algorithmic trading, GenAI would have no disadvantages since it relies strictly on learned patterns and rules and will execute trades based on them (Feuerriegel et al., 2024), the use of artificial intelligence to automate algorithmic trading presents a significant problem that needs to be taken into account, namely the risk of increasing market volatility. Because large datasets are full of patterns, GenAI models can execute trading decisions at high speed (Koshiyama et al., 2020; Viktor Manahov and Hanxiong Zhang, 2019). The result could very well be synchronized action from multiple AI systems acting on similar signals, either buying or selling at the same time. This could amplify market movements and lead to sudden price swings or crashes, destabilizing financial markets and causing widespread financial repercussions.

## Fraud Detection and Risk Management

GenAI is already greatly improving fraud detection and risk management in financial services by introducing the newest techniques in the identification and hampering of fraudulent activities (Mishra, 2023; Singh and Ahuja, 2024). Traditional models of fraud detection, in many cases, rely on static rules that might not capture new or sophisticated methods of fraud. However, generative AI adapts to the constantly changing nature of the threats by learning from newer patterns of data in real time (Feuerriegel et al., 2024; Kalota, 2024).

The use of generative artificial intelligence in fraud detection enhances the process through real-time monitoring of transactions (Yuanming Ding et al., 2023). By perusing denotes transaction in real time, it can notice many instances of anomalies that would essentially denote fraud (Singh and Ahuja, 2024). This is a different kind of customer service automation from the above–discussed, in that it focuses more on improving interactions with customers. Although both applications make use of AI for data processing, fraud detection requires immediate action to prevent the losses that might potentially occur.

It also helps in higher-order risk profiling by predicting fraud trends in the future. It can model different scenarios of fraud and judge the likelihood of different types of fraudulent activities happening (Gupta et al., 2023). This proactive approach helps the financial institutions take mitigation measures to prevent those frauds from happening. This is different from what has been explained above as portfolio optimization, where artificial intelligence aids in balancing the investment risk against return. In fraud detection, however, it performs identification and mitigation of risk associated with fraudulent behavior.

Other applications include cybersecurity, where GenAI prevents cyber-attacks that lead to fraud (Mishra, 2023; Neupane et al., 2023). By monitoring network activities and detecting patterns out of the ordinary, AI systems can assist in efforts that block unauthorized access to sensitive financial data.

Generative AI also contributes to regulatory compliance in respect to fraud: it can automate the production of suspicious activity reports and assist financial institutions in meeting all legal requirements with respect to fraud monitoring and reporting (Gupta et al., 2023).

## Downsides of GenAI in Fraud Detection and Risk Management

One of the main limitations of using GenAI in fraud detection and risk management stems from the fact that for most users, AI systems are like *"black boxes"*, in some cases it is not clear to us how the system ended up making certain decisions (Grange et al., 2024; Huang et al., 2024). This can cause some problems in fraud detection and risk management since the AI system marks some transactions as fraudulent without giving much explanation for it, and therefore it may turn out difficult to act in full accord with regulation.

Another limitation can be the presence of false positives and false negatives (Luo et al., 2022). In fraud detection, a false positive refers to a situation where a normal transaction has been flagged as fraudulent, thus causing inconvenience for the customer (Koleva and Krcmar, 2018). A false negative occurs when a fraudulent transaction is not recognized and thus results in some kind of financial loss. Complete dependence on GenAI with no human oversight can also greatly increase these mistakes.

There are also concerns about data privacy and security (Zhang et al., 2022). The GenAI system needs substantial amounts of sensitive personal and financial data to function well (Cronin, 2024; Sadok et al., 2022). This makes them more vulnerable to data breaches or unauthorized access. The security line needs to be strong enough to ensure the protection of customer information by financial institutions.

Regulatory challenges also need to be considered, given that most countries are still changing laws and regulations governing the use of AI in financial services (Aniket Deshpande, 2024; Rakha, 2023). Financial institutions must work out the uncertain legal landscape and ensure that their AI systems conform to all guidelines. Failure to do so will bring in penalties and harm to reputation.

## Credit Scoring and Loan Underwriting

Credit scoring and loan underwriting are further revolutionized with increased access, fairness, and transparency in lending (Sadok et al., 2022; Takyar, 2023). While the previous discussions have underlined automation and personalization of financial services, the use of GenAI in credit evaluation brings in new dimensions: that of inclusivity and ethical consideration.

Another relevant contribution of generative AI involves the extension of financial inclusions (How et al., 2020; Sadok et al., 2022). Traditional credit scoring mechanisms normally shut out people with non-existent or thin credit histories, and those without conventional financial records. In this respect, generative artificial intelligence fills the gap by processing alternative information such as utility bill payments, rental histories, and most interestingly, even patterns of mobile phone use (Takyar, 2023). These unconventional indicators form the basis upon which AI models rate the creditworthiness of the underserved population, opening opportunities for them to get loans and create credit profiles.

Moreover, generative artificial intelligence makes lending decisions even fairer. Credit scoring can become discriminatory, allotting different scores to applicants of different genders, ethnic backgrounds, or socio-economic statuses. The GenAI models can be trained to reduce such bias by giving more attention to the relevant financial behaviors rather than demographic characteristics (Jain and Menon, 2023; Swati Sachan et al., 2019; Takyar, 2023). This will be in line with ethical considerations in lending and provide equal opportunities for all applicants.

Unlike customer service automation, which was targeted to improve the interaction rate between customers and financial institutions, the use of GenAI in credit scoring influences the very process of decision-making (Hentzen et al., 2022). It doesn't just speed up operations but also makes lending nondiscriminatory and fair.

Another key area is that of explanation and transparency of AI decisions (Grange et al., 2024; Huang et al., 2024). For instance, financial institutions should be able to disclose the reasoning for any credit approval or denial in a manner that applicants would understand. Designs for GenAI models can include providing understandable explanations for assessments so applicants understand their current financial standing and areas for improvement (Kim and Woo, 2022). This transparency leads to better relations between lenders and borrowers, even as it helps to meet the demands of regulators for fair lending practices.

While similar in scope to the risk management strategies – wherein GenAI predicts potential financial risk – the focus for credit scoring is on the individual borrower risk (Hentzen et al., 2022). Both applications analyze data with the aim of making predictions. However, credit scoring focuses on personal creditworthiness rather than more general financial anomalies.

Generative AI also supports real-time decisioning in loan underwriting (Swati Sachan et al., 2019; Takyar, 2023). The models can make immediate approvals or rejections by swiftly processing application data. This high speed makes the customer experience very different and much better, as the applicant will no longer have to wait days or weeks for a decision. This allows lenders to process a much higher volume of applications efficiently.

## Downsides of GenAI in Credit Scoring and Loan Underwriting

One of the key limitations is the possibility of biases in AI algorithms (Jain and Menon, 2023). If there are historical biases in the data used to train generative AI, this AI has the potential to discriminate against categories of people, even unconsciously. The effects can be unreasonable differences in loan applications or attrition rates, which can raise ethical and even legal issues of discrimination.

Another important concern pertaining to the application of GenAI in the financial services sector is that of data security (Singh and Ahlawat, 2023). Operationalizing AI systems requires exposing them to a colossal amount of personal and sensitive information regarding finances. If proper security is not maintained, this information might be used for purposes other than intended. Data breaches lead to identity theft, losses for customers, and damage to brand reputation on the part of the financial services provider (Zhang et al., 2022).

One more thing to consider is regulatory challenges (Aniket Deshpande, 2024). Laws and regulations in the financial industry are strict: they are put in place to protect consumers and maintain practices that are considered fair. The use of GenAI introduces new complications, as regulations may not have kept pace with the rapid development of AI technologies. The legal risks that might be faced by the financial institutions are that AI systems can make certain decisions not in full compliance with existing laws, particularly those which cannot easily be explained due to the *"black box"* nature of some AI models.

Besides, there is also an issue with the aspect of transparency. Most of the time, the GenAI models are complicated and, hence, very difficult to understand or, better still, be explained how they came about in a certain decision. The lack of transparency when using this generation of AI could potentially build mistrust among clients, as well as present difficulties for institutions to adequately explain their decisions to regulators (Banovic et al., 2023). AI systems should, in essence, be transparent so that their decision-making process is auditable and understandable.

## Synthesis on the Impact of GenAI on Financial Services

The main objective of this chapter was to perform the literature review with the search for answering how GenAI impacts financial services in the attempt to define the usefulness of generative artificial intelligence in the streamlining of various aspects of financial services. Of course, it would appear to be a technology with potential to revolutionize the financial sector in customer service, fraud detection, personalized financial planning, portfolio management, credit scoring and other financial services. It not only improves operation efficiency because of the technology, but also personalized services can be offered that might lead to an improved customer experience and better financial decision-making.

Probably the most striking advantage of GenAI in financial services is its use for the automation of routine tasks, especially in customer service. AI-driven chatbots and virtual assistants enable each financial organization to offer 24/7 customer support by answering frequently asked questions and even providing personalized financial advice. This reduces the demand for human agents, thus lowering operation costs while response times and customer satisfaction grow. The multitasking capability of GenAI, with the ability to handle multiple queries at once, will enable an institution to scale up its services and be efficient for more customers.

Fraud detection and risk management also have found one valuable tool in GenAI. It can focus on huge data analysis in real time, picking out suspicious patterns for fraud detection at a much faster rate than normally allowed. Further, such real-time monitoring allows financial institutions to mitigate potential risks and reduce financial losses. Finally, the predictive capability of the technology allows for better risk profiling, enabling these institutions to take proactive steps toward the protection of their clients and assets.

Another important use of GenAI is in financial planning and portfolio optimization at the level of an individual. Based on analyses of the financial data of a particular person, GenAI makes recommendations about how a person earns and spends money and can set specific goals regarding finances. On the other hand, such personalization of financial planning and the resulting portfolio optimization could make the advice more relevant to customers and thereby help them make better financial decisions. Similarly, with portfolio optimization, the capabilities of GenAI will enable it to seek out the best investment opportunities through real-time market data to help investors reap higher returns with reduced risk.

These are obvious gains, however, the chapter also identified a few challenges: integrating GenAI in financial services results in the loss of the human touch in customer service, ethical issues on leaked data privacy, and biased AI-driven decision-making processes. Besides, overdependence on the automation of systems may reduce the financial literacy of customers who may depend more on AI in managing their finances.

## Research Results

The main purpose of the paper was to analyze and synthesize the literature to define generative artificial intelligence and its impact on the financial services industry, highlighting the usefulness of implementing the technology as well as some drawbacks of its use in some financial services. The work also had several secondary objectives.

One of the secondary objectives aimed to define the essence of generative artificial intelligence and its purpose. This goal has been achieved in chapter two, which, reviewing the literature, defines GenAI as a technology that generates new content, like text, images, audio or data models based on the patterns the system learns from large amounts of data. GenAI differs from more common AI in that it automates content creation and decision-making-things that have changed many business practices across industries. It automates tasks, streamlines processes, and offers personalized experiences through GenAI in financial services, thereby dramatically changing how such institutions operate. The literature review has provided a detailed insight into the major characteristics of GenAI, showing that it is not just a technology that enables operational improvements, but a transformative technology that reshapes industries.

The second objective was to understand the usefulness of GenAI in improving the operational efficiency of financial services. This objective has also been fully attained by the analysis of various applications of GenAI in financial operations. It has also been observed that GenAI automates several critical tasks in financial institutions, such as automation of customer service, portfolio management, and fraud detection. For instance, AI-powered chatbots were deployed to handle customer inquiries and provided customized advice in real time. These can be done by the AI-powered systems continuously without any interference from humans, thus enabling quicker and better service for customers. Also, by doing deep data analysis and finding patterns, GenAI is helping financial institutions optimize resource allocation, enhance the accuracy of decision-making, and decrease operational costs. These findings further establish the fact that GenAI is highly important not only in enhancing operational efficiency but also ensuring a speedy process, while reducing the overall work pressure of human employees.

The third objective was to highlight the pros and cons of integrating GenAI into financial services. Through careful analysis, this objective was also achieved. It seemed that the benefits of using GenAI are great because it enhances the productivity of personnel by automating repetitive tasks and providing real-time insight, therefore allowing a financial institution to offer highly personalized services to its clients. It has also been determined to enhance customer satisfaction by way of personalized counsel and quick responses to inquiries. On the other hand, with these benefits, several dilemmas were observed. The first major drawback of GenAI is the lack of human empathy when serving customers. As efficient as AI-driven chatbots and other systems are, they cannot portray the emotional intelligence that human advisors can portray. Further, use of GenAI also opens many issues relating to data privacy, as these are systems which must have unlimited access to sensitive information to function effectively. Therein also lies the danger of various biases from algorithms that can make biased or incorrect decisions when dependency for something like credit scoring or loan underwriting decisions arises.

Regarding hypotheses, the first one was that generative AI could enhance operational efficiency, accuracy, and productivity in finance through automation of processes and decisions. The research results confirm that GenAI improves the efficiency of operations by automating tasks, thus enabling financial institutions to focus on more complex and value-based tasks. GenAI's ability to process large data sets and make decisions in real time also increases the accuracy of decisions. Indeed, several studies showed that the financial institutions where the technology has been used have witnessed reduced operational costs and improved customer satisfaction, proving that GenAI is beneficial also in terms of efficiency and productivity.

The second hypothesis was that through process automation, improving customer service, and optimizing resources, generative AI could decrease the cost of delivering financial services. This hypothesis proved true. Essentially, in automating queries from customers, for instance, GenAI decreases the number of human agents required in every single interaction, hence cutting costs of labor and improving productivity. Indeed, the use of chatbot AI systems improves customer service by offering speed and personalization of response, thus further lowering costs related to human-driven customer service. It was noted that GenAI helps financial institutions optimize resource allocation to focus resources on high-priority tasks while keeping operations costs to a minimum. This verifies that the overall cost of service delivery with GenAI will be reduced.

Third, it was hypothesized that generative AI could enrich personalized customer experiences through offers of tailored financial advice and real-time insights, but associated data privacy, bias, and ethical issues may be a risk. This hypothesis was therefore only partially validated. The research found that GenAI enhances personalized customer experiences by providing personalized financial advice tailored to an individual's financial goals, spending habits, and risk appetite by analyzing big data. This is one of the strongest features of GenAI, whereby, through this, the financial institutes can meet the needs of their clients more precisely than before. On the other hand, the research confirmed the risks of AI: mainly those concerning data privacy and algorithmic biases. The use of personal and sensitive financial data to create insights raises questions about how such data is processed and covered. Data biases in the dataset from which AI models are trained result in several decisions that are often biased or unfair, such as loan approvals and credit scorings. Concerns over ethics also highlighted issues of transparency and accountability of the AI systems since most of the models were also *"black box"* in nature, where decisions arrived at were rather not evident.

Research results highlight that GenAI has proven useful in the world of financial services by increasing efficiency, reducing costs and making better decisions. However, for responsible use, issues of data privacy, ethical decision making, and customer interface without sentiment or empathy need to be addressed. While there are significant benefits from GenAI, a judicious balance between automation and human oversight – empathy – must be maintained for successful integration within the industry.

## Discussions

Generative artificial intelligence has the potential to transform financial services fundamentally, but its integration raises several issues that go beyond the technological sphere and require reflection on the ethical, legal and social implications. Although the literature provides a detailed picture of the technological benefits of GenAI, some gaps remain evident, particularly with regard to the actual effects of the implementation of these technologies in the financial environment, the level of user training, and the risks associated with automated decision making.

First of all, there is a lack of empirical research directly analyzing the impact of GenAI on the relationship between financial institutions and customers. Most existing studies are based on theoretical analysis or extrapolation of general trends, without providing sufficient concrete examples from practice. At the same time, there is a lack of in-depth examination of cultural, institutional or legislative differences that may influence how the GenAI is perceived and applied in different jurisdictions.

Both legally and ethically, the implementation of generative artificial intelligence raises several important challenges. Among the fundamental concerns is the lack of transparency in decision making because many of the models used are not transparent and users don't know where some recommendations of decisions come from. This is an obstacle that threatens the users' credibility. GenAI models can also repeat or even amplify existing biases in historical data, which can lead to unintentional discrimination, particularly in credit scoring or lending. The use of personal data to deliver results – frequently described as highly sensitive – imposes additional burdens on financial institutions in terms of data protection and cybersecurity procedures. Meanwhile, the regulatory landscape is still developing, and the lack of clear guidance on the application of artificial intelligence in the financial sectors leads to uncertainty and legal gaps for institutions.

A significant element highlighted in the literature reviewed is the need to develop digital literacy among users, both customers and employees in the financial sector. Technologies based on generative artificial intelligence can be perceived either as perfect solutions or as systems that are difficult to understand, which can lead to overconfidence in the results offered or, on the contrary, to rejection of their use. In this context, it is important that financial education programs include accessible information about how these systems work, about possible technological risks, and about users' rights and responsibilities in relation to emerging digital technologies.

In order to summarize the practical implications of using GenAI in the financial sector, it may be useful to present a comparative overview of the advantages and disadvantages identified in the literature:

**Table 1.** Advantages and disadvantages of implementing GenAI in financial services

| Advantages | Disadvantages |
|---|---|
| Automation of repetitive processes and reduction of operational costs | Lack of empathy and understanding of human context |
| Real-time personalized recommendations | Risk of inaccurate or biased decisions |
| Efficiency in risk analysis and fraud detection | Risks related to the confidentiality of personal data |
| Continuous customer support through automated system | Lack of transparency in decision making processes |
| Expanded access to financial services for individuals without banking history | Legal challenges regarding regulatory compliance |

In this context, the implementation of GenAI into the digital infrastructure of financial institutions should not be understood only as a technological evolution, but as a complex process that involved balancing innovation with principles of responsibility. It is important that IT developers, financial institutions, regulators and users work together to ensure a secure, ethical and fair implementation. Only through collaboration between all stakeholders it is possible to build a sustainable framework in which GenAI can effectively enable progress without undermining fundamental values such as fairness, transparency and user protection.

## Conclusions and Future Research Directions

Generative artificial intelligence is a technology that is strongly impacting today's society, especially the business environment. It has great potential, offering the possibility for organizations to streamline various processes by automating them, while also increasing their accuracy and speed. In the field of financial services, the literature is vast, encompassing various case studies, both on the usefulness of generative artificial intelligence and on the challenges and downsides of digitizing processes with the help of this technology. The current paper is a synthesis of the literature, its aim being to define the technology and its impact on financial services.

Thus, it was highlighted that GenAI is capable of streamlining processes such as offering customer service and personalized financial planning, portfolio optimization, risk management and fraud detection, algorithmic tracking, credit scoring and loan underwriting. The paper also highlighted challenges such as ensuring data security, and the correctness of decisions made by the GenAI system.

Given that the results of the paper were formulated based on the literature review, a future direction would be to conduct research based on primary data, thus collecting data using tools such as questionnaire or interview from companies in a particular industry that have streamlined their business processes by integrating GenAI. The aim of this approach would be to identify the impact of GenAI in a particular sector directly from the experiences of organizations, thus contributing to the literature with new data on the usefulness of generative AI.

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