

CUSTOMER SWITCHING BEHAVIOR

—

SELECTED ESSAYS ON DIGITAL SERVICES

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Abkürzungsverzeichnis

ACR	Association for Consumer Research
AI	artificial intelligence
AMA	American Marketing Association
AVE	average variance extracted
B2B	business-to-business
CA	conversational agent
CA	Cronbach's alpha
CB-SEM	covariance-based structural equation modeling
CEI	composite equivalence index
CFA	confirmatory factor analysis
CFI	comparative fit index
CI	confidence interval
CMB	common method bias
CR	composite reliability
CRM	customer relationship management
d. h.	das heißt
DoF	degrees of freedom
e.g.	exempli gratia
engl.	englisch
et al.	et alii
e. V.	eingetragener Verein
HA	human agent
HTMT	heterotrait-monotrait

i.e.	id est
IL	indicator loading
IS	information system
KI	Künstliche Intelligenz
LGCM	latent growth curve model
LM	linear model
MAE	mean absolute error
MASEM	meta-analytic structural equation modeling
NPS	net promoter score
OSMASEM	one-stage meta-analytic structural equation modeling
PA	possible actions
PANAS	positive and negative affect schedule
PLS-SEM	partial least squares structural equation modeling
PPM	push-pull-mooring
RMSE	root mean square error
RMSEA	root mean square error of approximation
SEM	structural equation modeling
SL	self-location
SPES	spatial presence experience scale
SPSM	Service Provider Switching Model
SRMR	standardized root mean square residual
SUIS	spontaneous use of imagery scale
TCMCC	Three-Component Model of Customer Commitment
TLI	Tucker-Lewis index

TPB	Theory of Planned Behavior
vgl.	vergleiche
VHB	Verband der Hochschullehrerinnen und Hochschullehrer für Betriebswirtschaft
VIF	variance inflation factor
VR	Virtuelle Realität (engl. virtual reality)
vs.	versus
VSS	video streaming service
Wh	watt-hour
z. B.	zum Beispiel

1 Einleitung

1.1 Problemstellung und Zielsetzung der Arbeit

Die **Rahmenbedingungen für Unternehmen** unterliegen einem kontinuierlichen Wandel und haben sich in den vergangenen Jahrzehnten aufgrund vielfältiger Entwicklungen grundlegend verändert (Bruhn, 2022; Meffert et al., 2024). Zur Verdeutlichung der dieser Arbeit zugrunde liegenden Problemstellung sowie der daraus abgeleiteten Zielsetzung werden im Folgenden drei dieser Entwicklungen¹ näher beschrieben.

Erstens ist in vielen Märkten die frühere Angebotsknappheit einem Überangebot gewichen, das Nachfragern² eine große Auswahl aus einer Vielzahl vergleichbarer Produkte und Dienstleistungen ermöglicht (Meffert et al., 2024). Obwohl Konsumenten³ die große Auswahl an Optionen grundsätzlich als vorteilhaft wahrnehmen, geraten sie zunehmend sogar in sogenannte Choice-Overload-Situationen, in denen die Vielzahl an Auswahlmöglichkeiten überfordernd wirkt (Gröppel-Klein & Kroeber-Riel, 2025). Dieser **Wandel vom Verkäufer- hin zum Käufermarkt** bedeutet für Unternehmen, dass nicht länger die Produktionskapazität, sondern der Absatzbereich den Engpassfaktor bildet (Bruhn et al., 2022; Meffert et al., 2024). Vor dem Hintergrund des resultierenden Verdrängungswettbewerbs gewinnt ein differenzierter Marktauftritt an Bedeutung, da er ein akquisitorisches Potenzial schafft und Unternehmen ermöglicht, sich im intensiven Wettbewerb um Kunden gegenüber der Konkurrenz zu positionieren (Gröppel-Klein & Kroeber-Riel, 2025; Gutenberg, 1955; Meffert et al., 2024). Eine zentrale Voraussetzung für eine erfolgreiche Differenzierung ist eine ausgeprägte Kundenorientierung aufseiten der Unternehmen (Bruhn, 2022). Unternehmen, die Marktanteile sichern oder gewinnen wollen, müssen nicht nur verstehen, was Kunden bindet, sondern auch, was sie zu einem Wechsel bewegt (Keaveney, 1995). Eine umfangreiche Kenntnis der Determinanten des Kundenwechselverhaltens ist daher für

¹ Die Auswahl dieser drei Entwicklungen basiert darauf, dass sie langfristig, weitreichend und tiefgreifend wirken. Der Wandel vom Verkäufer- zum Käufermarkt, die Tertiarisierung sowie die Digitalisierung sind Entwicklungen, die bereits über einen langen Zeitraum hinweg bestehen, eine große Zahl von Unternehmen betreffen und deren Rahmenbedingungen in erheblichem Ausmaß verändern, was unter anderem durch ihre wiederkehrende Thematisierung in einschlägiger Literatur hervorgehoben wird (vgl. z. B. Bruhn, 2022; Meffert et al., 2018; Meffert et al., 2024; Olbrich, 2022).

² Im Interesse einer vermutlich besseren Lesbarkeit wird in dieser Arbeit nicht ausdrücklich zwischen geschlechtsspezifischen Personenbezeichnungen differenziert. Sämtliche personenbezogenen Bezeichnungen gelten gleichermaßen für alle Geschlechter.

³ In Anlehnung an Meffert et al. (2024) und Kenning (2021) werden die Begriffe Konsument, Kunde, Nutzer und Verbraucher in dieser Arbeit synonym verwendet.

Unternehmen essenziell – sowohl zur Bindung bestehender Kunden als auch zur gezielten Ansprache von wechselbereiten Kunden bei der Konkurrenz (Bansal et al., 2005).

Zweitens ist in vielen Ländern seit Jahrzehnten ein tiefgreifender Strukturwandel zu einer Dienstleistungsgesellschaft zu beobachten (Klodt et al., 1997; Schwahn et al., 2018). Dieser Wandel – häufig als **Marsch in die Dienstleistungsgesellschaft** oder **Tertiarisierung** bezeichnet (Fourastié, 1954; Klodt et al., 1997; Meffert et al., 2018) – geht damit einher, dass sich im Zuge der wirtschaftlichen Entwicklung einer Volkswirtschaft die Schwerpunkte wirtschaftlicher Aktivität zunächst vom primären Sektor (Agrarwirtschaft) auf den sekundären Sektor (Industrie und Baugewerbe) und schließlich auf den tertiären Sektor (Dienstleistungen) verlagern (Klodt et al., 1997; Schwahn et al., 2018). Die Tertiarisierung in Deutschland zeigt sich deutlich in der sektoralen Beschäftigungsentwicklung: Während 1950 noch etwa 25 % der Erwerbstätigen in der Agrarwirtschaft tätig waren, sank dieser Anteil bis 2017 auf etwa 1 % (Schwahn et al., 2018). Der sekundäre Sektor erreichte 1965 mit 49 % seinen Höchststand, ging jedoch bis 2017 auf 24 % zurück (Schwahn et al., 2018). Im Gegenzug gewann der tertiäre Sektor stetig an Bedeutung und stellte 2017 mit etwa 75 % aller Erwerbstätigen den größten Wirtschaftsbereich dar (Schwahn et al., 2018). Ein ähnlicher sektoraler Wandel lässt sich auch in anderen Ländern wie Frankreich, Japan oder den Vereinigten Staaten von Amerika beobachten (Schwahn et al., 2018). Vor dem Hintergrund der wachsenden Bedeutung von Dienstleistungen für die Wirtschaft ergibt sich folgerichtig eine zunehmende Relevanz von Fragestellungen im Bereich des Dienstleistungsmarketings (Meffert et al., 2018).

Drittens verändert die seit Jahrzehnten kontinuierlich fortschreitende **Digitalisierung**⁴ Wirtschaft und Gesellschaft tiefgreifend (Legner et al., 2017; Van Veldhoven & Vanthienen, 2022). Digitale Technologien durchdringen zunehmend alle Lebensbereiche und sind aus dem Alltag von Konsumenten und Unternehmen nicht mehr wegzudenken (Plekhanov et al., 2023; Van Veldhoven & Vanthienen, 2022). Die steigende Relevanz digitaler Technologien lässt sich anhand aktueller

⁴ Der Begriff Digitalisierung (engl. digitalization) lässt sich definieren als „the manifold sociotechnical phenomena and processes of adopting and using these [digital] technologies in broader individual, organizational, and societal contexts“ (Legner et al., 2017, S. 301). Davon klar abzugrenzen ist der Begriff Digitisierung (engl. digitization), der „the technical process of converting analog signals into a digital form, and ultimately into binary digits“ beschreibt (Legner et al., 2017, S. 301). Weniger eindeutig abgrenzbar ist hingegen der Begriff digitale Transformation (engl. digital transformation), der je nach Autor entweder mit Digitalisierung gleichgesetzt wird (Legner et al., 2017), darüber hinausgeht (Van Veldhoven & Vanthienen, 2022) oder sich ausschließlich auf den Unternehmenskontext bezieht (Plekhanov et al., 2023). In dieser Arbeit werden die Begriffe Digitalisierung und digitale Transformation als synonym erachtet.

Zahlen verdeutlichen: Im Jahr 2024 nutzten weltweit 67,6 % der Bevölkerung das Internet – ein deutlicher Anstieg im Vergleich zu 38,1 % im Jahr 2014 (International Telecommunication Union, 2024). In Deutschland lag der Anteil der Internetnutzenden im Jahr 2024 sogar bei 96 % (Statistisches Bundesamt, 2024b). In nahezu allen Branchen gewinnen digitale gegenüber nicht-digitalen Alternativen an Bedeutung: So nutzten im Jahr 2024 rund 67 % der deutschen Bevölkerung Online-Banking, 58 % soziale Netzwerke und 78 % das Internet zur gezielten Informationssuche über Produkte und Dienstleistungen (Statistisches Bundesamt, 2024a). Zwei in der Konsumentenverhaltensforschung besonders relevante digitale Technologien der letzten Jahre sind die Künstliche Intelligenz (KI) und die Virtuelle Realität (VR), die exemplarisch verdeutlichen, wie rasant sich digitale Technologien entwickeln und wie tiefgreifend sie das Konsumentenverhalten verändern können (Gröppel-Klein & Kroeber-Riel, 2025). Während es vor wenigen Jahren noch wie Science-Fiction klang, dass KI Kunst erzeugt, sich als Mensch ausgibt, zentrale Lebensentscheidungen trifft und mehr über Menschen weiß als sie selbst, gehört all dies inzwischen zum Alltag (Harari, 2024). Gleichermaßen ermöglicht VR Konsumenten heute realitätsnahe, virtuelle Erlebnisse wie den Einkauf in Geschäften, den Besuch eines Bauernhofs oder die Teilnahme an einer Modenschau in Paris – und all das bequem von zu Hause aus mithilfe eines VR-Headsets (Gröppel-Klein & Kroeber-Riel, 2025; Peukert, 2019; Marx et al., 2025). Insofern stellt sich für Unternehmen nicht mehr die Frage, ob sie sich mit der Digitalisierung auseinandersetzen sollten, sondern vielmehr, wie sie diese gezielt gestalten können, um wettbewerbsfähig zu bleiben.

Die drei beschriebenen Entwicklungen – der Wandel vom Verkäufer- zum Käufermarkt, die Tertiärisierung sowie die Digitalisierung – prägen gemeinsam maßgeblich die heutigen Rahmenbedingungen für Unternehmen (Bruhn, 2022; Meffert et al., 2018; Meffert et al., 2024; Olbrich, 2022). Vor diesem Hintergrund gewinnt ein umfangreiches Verständnis des Kundenwechselsverhaltens im digitalen Dienstleistungskontext an Bedeutung. Daraus ergeben sich drei zentrale Forschungsfragen, welche diese Arbeit adressiert:

1. **Forschungsfrage 1:** *Wie lässt sich Kundenwechselsverhalten im Dienstleistungskontext definieren und von verwandten Konzepten abgrenzen?*
2. **Forschungsfrage 2:** *Welche theoretischen Ansätze eignen sich zur Erklärung des Kundenwechselsverhaltens im Dienstleistungskontext?*

3. **Forschungsfrage 3:** *Was sind die Determinanten des Kundenwechselverhaltens im digitalen Dienstleistungskontext?*

Während Definition und theoretische Fundierung zunächst im allgemeinen Dienstleistungskontext behandelt werden, erfolgt die Analyse der Determinanten weitestgehend im Kontext digitaler Dienstleistungen, die den spezifischen Untersuchungsgegenstand dieser Arbeit bilden.⁵ Die übergeordnete Zielsetzung der Arbeit besteht darin, diese drei Forschungsfragen zu beantworten und auf Basis der gewonnenen Erkenntnisse fundierte theoretische, praktische sowie gesellschaftliche und politische Implikationen abzuleiten.

1.2 Aufbau der Arbeit

Um die Zielsetzung zu erfüllen und die drei Forschungsfragen beantworten zu können, gliedert sich die vorliegende Arbeit in sechs Kapitel.

In **Kapitel 2** werden die begrifflichen und theoretischen Grundlagen für die weiteren Ausführungen dargelegt. In Kapitel 2.1 wird Wechselverhalten zunächst als allgemeines betriebswirtschaftliches Phänomen eingeführt, das sich auf verschiedene Anspruchsgruppen eines Unternehmens beziehen kann (Kapitel 2.1.1). Anschließend wird das auf die Anspruchsgruppe der Kunden bezogene Phänomen des Kundenwechselverhaltens beschrieben, vom Begriff der Kundenabwanderung abgegrenzt und typologisiert (Kapitel 2.1.2). In Kapitel 2.2 wird das Relationship Marketing als Teil des modernen Marketingverständnisses eingeführt (Kapitel 2.2.1). Ausgehend von der Abgrenzung zum transaktionsorientierten Marketing wird dessen beziehungsorientierte Ausrichtung erläutert, die Kundenakquisition, Kundenbindung und Kundenrückgewinnung als zentrale Ziele umfasst. Dabei wird die ökonomische Relevanz langfristiger Kundenbeziehungen anhand direkter und indirekter Erfolgswirkungen aufgezeigt. Anschließend wird die daraus abgeleitete Bedeutung des Kundenwechselverhaltens im Kontext des Relationship Marketing herausgearbeitet (Kapitel 2.2.2). In Kapitel 2.3 werden zunächst die Besonderheiten digitaler Dienstleistungen dargelegt (Kapitel 2.3.1). Nach einer allgemeinen Definition und Beschreibung von Dienstleistungen wird der Begriff digitaler Dienstleistungen abgegrenzt und auf rein digitale

⁵ Dieses Vorgehen erscheint sinnvoll, da sich die grundlegende Definition und theoretische Fundierung des Kundenwechselverhaltens im allgemeinen Dienstleistungskontext auch auf digitale Dienstleistungen als spezifischen Untersuchungsgegenstand übertragen lassen. Die Analyse der Determinanten des Kundenwechselverhaltens erfolgt jedoch vor dem Hintergrund der zuvor beschriebenen Entwicklungen kontextspezifisch an der zunehmend relevanter werdenden Schnittstelle von Tertiarisierung und Digitalisierung – den digitalen Dienstleistungen (Meffert et al., 2018).

Dienstleistungen fokussiert. Dabei werden spezifische Charakteristika erläutert. Anschließend werden die daraus resultierenden betriebswirtschaftlichen Besonderheiten beschrieben (Kapitel 2.3.2). Darauf aufbauend wird die Bedeutung dieser Besonderheiten für das Kundenwechselverhalten im Kontext digitaler Dienstleistungen herausgearbeitet (Kapitel 2.3.3). In Kapitel 2.4 werden theoretische Ansätze zur Erklärung des Kundenwechselverhaltens vorgestellt. Zunächst wird die Notwendigkeit eigenständiger theoretischer Ansätze zur Erklärung von Kundenwechselverhalten herausgearbeitet. Anschließend wird die Entwicklung der Forschung von ersten empirischen Untersuchungen über die Phase der Modellformulierung bis hin zur Phase der Modellprüfung nachgezeichnet. Die im Rahmen der Modellformulierung beschriebenen Modelle werden dargestellt und vergleichend gegenübergestellt.

In **Kapitel 3** werden die der vorliegenden Arbeit zugrunde liegenden sechs Beiträge zusammengefasst und systematisch eingeordnet.

Das **Kapitel 4** enthält anschließend die Präsentation der einzelnen Beiträge in voller Länge.

Das **Kapitel 5** bündelt die zentralen Ergebnisse der Arbeit, leitet daraus Implikationen für verschiedene Interessensgruppen ab und diskutiert bestehende Limitationen sowie Potenziale für zukünftige Forschung. Zunächst erfolgt eine Zusammenfassung der in der vorliegenden Dissertation gewonnenen Erkenntnisse (Kapitel 5.1). Darauf aufbauend folgen die theoretischen Implikationen (Kapitel 5.2), die praktischen Implikationen (Kapitel 5.3) sowie die gesellschaftlichen und politischen Implikationen (Kapitel 5.4). Abschließend werden die Limitationen der Arbeit erörtert und darauf basierend Ansatzpunkte für zukünftige Forschung aufgezeigt (Kapitel 5.5).

Das **Kapitel 6** beinhaltet schließlich ein Fazit der vorliegenden Arbeit.

2 Begriffliche und theoretische Grundlagen

2.1 Wechselverhalten

2.1.1 Wechselverhalten als betriebswirtschaftliches Phänomen

Unternehmen agieren nicht isoliert, sondern in einem Netzwerk aus Anspruchsgruppen – den sogenannten Stakeholdern (Freeman, 1984; Freeman et al., 2010; Meffert et al., 2024). Als **Stakeholder** gilt „any group or individual who can affect or is affected by the achievement of an organization’s purpose“ (Freeman, 1984, S. 53). Zu den zentralen Stakeholdern zählen insbesondere Kunden, Mitarbeiter, Lieferanten und Eigentümer (Freeman, 1984). Jede dieser Anspruchsgruppen steht in einer Austauschbeziehung mit dem Unternehmen und kann sich im Zeitverlauf für einen Wechsel entscheiden – sei es im Hinblick auf Produkte, Dienstleistungen, Arbeitsverhältnisse, Geschäftsbeziehungen oder Kapital.

Wechselverhalten (engl. switching behavior) bezeichnet in diesem Zusammenhang die Entscheidung eines Stakeholders, eine bestehende Beziehung zu einem Unternehmen zu verändern und sich einer alternativen Option zuzuwenden (Bansal et al., 2005; Cotton & Tuttle, 1986; Keaveney, 1995; Meier & Maier, 2023; Wagner & Friedl, 2007). Das Wechselverhalten von Stakeholdern kann unterschiedliche Ursachen, Ausprägungen und Konsequenzen haben, ist jedoch stets von betriebswirtschaftlicher Relevanz, da es den Erfolg des Unternehmens beeinflusst (Freeman, 1984). So werden Kunden beispielsweise zwischen Dienstleistungsanbietern wechseln, wenn sie unzufrieden sind oder attraktivere Alternativen wahrnehmen (vgl. z. B. Bansal et al., 2005). Mitarbeiter entscheiden sich unter bestimmten Bedingungen für einen Arbeitgeberwechsel, etwa bei Unzufriedenheit mit dem Gehalt, mangelnder Wertschätzung durch Vorgesetzte oder einem als wenig erfüllend empfundenen Arbeitsinhalt (vgl. z. B. Cotton & Tuttle, 1986). Auch Lieferanten prüfen regelmäßig, ob eine Verlagerung ihrer Geschäftsbeziehungen wirtschaftlich vorteilhaft ist, beispielsweise, wenn alternative Abnehmer bessere Konditionen bieten (vgl. z. B. Wagner & Friedl, 2007). Schließlich treffen Eigentümer Reallokationsentscheidungen mit Blick auf ihr investiertes Kapital, wenn sich etwa Renditeerwartungen oder Risikoeinschätzungen verändern (vgl. z. B. Meier & Maier, 2023).

Ogleich Wechselverhalten somit ein vielseitiges betriebswirtschaftliches Phänomen darstellt, liegt der Fokus der vorliegenden Arbeit auf dem Wechselverhalten von Kunden. Unter den

verschiedenen Stakeholdern hat der Kunde eine besondere Stellung, da der Zweck eines Unternehmens primär darin besteht, einen Kunden zu schaffen (Drucker, 1954). Nur durch zahlungsbereite Kunden kann ein Unternehmen Umsatz generieren und bestehen (Drucker, 1954). Im Marketing kommt dem Kunden darüber hinaus eine zentrale Bedeutung zu, da alle marktorientierten Unternehmensaktivitäten auf ihn ausgerichtet sind (Meffert et al., 2024). In dem folgenden Kapitel wird daher das **Kundenwechselverhalten** näher beschrieben und typologisiert.

2.1.2 Kundenwechselverhalten

In der Marketingforschungsliteratur bezeichnet der Begriff **Kundenwechselverhalten** (engl. customer switching behavior) im Dienstleistungskontext das Phänomen, dass sich ein Kunde bei der Auswahl aus mehreren Dienstleistungen für eine andere als die bisher genutzte entscheidet (Keaveney, 1995). Während das Kundenwechselverhalten explizit den Wechsel zu einer anderen Dienstleistung beschreibt, bezieht sich der Begriff der **Kundenabwanderung** (engl. customer defection) im Dienstleistungskontext auf das Einstellen der Nutzung einer Dienstleistung (Reichheld & Sasser, 1990; Michalski, 2002) – ohne darüber Aufschluss zu geben, ob der Kunde stattdessen zu einer anderen Dienstleistung wechselt oder die Inanspruchnahme generell beendet. Ein Kunde kann beispielsweise sein Abonnement bei einem Streamingdienst wie Netflix kündigen. Falls er daraufhin zu einem alternativen Streamingdienst wie Disney+ oder Apple TV+ wechselt, handelt es sich um Kundenwechselverhalten. Falls er sich hingegen entscheidet, gar keinen Streamingdienst mehr zu nutzen, liegt Kundenabwanderung vor. Kundenwechselverhalten setzt demnach eine Kundenabwanderung voraus und ist somit als umfassenderer Begriff einzuordnen.

Beim Kundenwechselverhalten lässt sich zwischen einer teilweisen und einer vollständigen Ausprägung unterscheiden (Ye & Potter, 2011). Ein **teilweiser Wechsel** liegt vor, wenn der Kunde zusätzlich zu einer neuen Dienstleistung weiterhin auch die bisherige nutzt, deren Nutzung jedoch zugunsten der neuen Dienstleistung reduziert wird (Ye & Potter, 2011). Ein **vollständiger Wechsel** hingegen beschreibt den Fall, dass der Kunde die ursprüngliche Dienstleistung vollständig durch eine alternative ersetzt (Ye & Potter, 2011). Diese Unterscheidung ist insbesondere im digitalen Dienstleistungskontext relevant, in dem die parallele Nutzung verschiedener Angebote weit verbreitet ist (Ye & Potter, 2011). Ein teilweiser Wechsel liegt beispielsweise vor, wenn ein Kunde sein bestehendes Netflix-Abonnement beibehält, jedoch einen Teil seiner Streamingzeit auf

Disney+ verlagert. Beendet der Kunde hingegen sein Netflix-Abonnement und nutzt fortan ausschließlich Disney+, handelt es sich um einen vollständigen Wechsel.

Darüber hinaus weist die empirische Marketingforschung auf ein weiteres Differenzierungsmerkmal des Kundenwechsels hin: die Unterscheidung zwischen Anbieterwechseln und Technologiewechseln (Marx, 2025). Ein **Anbieterwechsel** liegt vor, wenn ein Kunde von einem Dienstleistungsanbieter zu einem anderen wechselt, dabei jedoch die zugrunde liegende Technologie gleich bleibt (Marx, 2025). Beispiele hierfür sind der Wechsel zwischen Cloud-Speicher-Diensten wie Microsoft OneDrive und Google Drive (vgl. z. B. Cheng et al., 2019) oder der Wechsel zwischen Instant-Messaging-Diensten wie WhatsApp und Telegram (vgl. z. B. Sun et al., 2017). Demgegenüber liegt ein **Technologiewechsel** vor, wenn ein Kunde eine Dienstleistung durch eine andere ersetzt, die auf einer anderen Technologie basiert (Marx, 2025). Technologie kann in diesem Zusammenhang definiert werden als „resources, tools, processes, personnel, and systems developed to perform tasks and create immediate particular, and personal and/or competitive advantages in a given ecological, economic, and social context“ (Bush, 1981, S. 1). Beispiele für Technologiewechsel sind der Wechsel von Barzahlung zu Mobile Payment (vgl. z. B. Hsieh, 2021) oder der Wechsel von ortsgebundener Gesundheitsberatung in einer Arztpraxis zu telemedizinischer Gesundheitsberatung per Videochat (vgl. z. B. Pan et al., 2023). Bei Technologiewechseln steht die Technologie im Vordergrund und der konkrete Anbieter spielt eine untergeordnete Rolle (Marx, 2025).

Die aus den zuvor dargelegten Unterscheidungen resultierende **zweidimensionale Typologie**, die zwischen teilweisem und vollständigem Wechsel sowie zwischen Anbieter- und Technologiewechsel unterscheidet, ist in Tabelle 1 dargestellt.

	Anbieterwechsel	Technologiewechsel
Teilweiser Wechsel	Teilweiser Anbieterwechsel	Teilweiser Technologiewechsel
Vollständiger Wechsel	Vollständiger Anbieterwechsel	Vollständiger Technologiewechsel

Tabelle 1: Typen von Kundenwechselsverhalten

Quelle: Eigene Darstellung

2.2 Relationship Marketing

2.2.1 Relationship Marketing als Teil des modernen Marketingverständnisses

Gemäß der **klassischen, ökonomischen Interpretation** umfasst **Marketing** „die Planung, Koordination und Kontrolle aller auf die aktuellen und potenziellen Märkte ausgerichteten Unternehmensaktivitäten“ (Meffert, 1974, S. 8). Die Unternehmensziele sollen diesem Verständnis zufolge durch eine dauerhafte Befriedigung der Kundenbedürfnisse verwirklicht werden (Meffert, 1974). Gemäß der **modernen, erweiterten Interpretation** ist Marketing „an organizational function and a set of processes for creating, communicating and delivering value to customers and for managing customer relationships in ways that benefit the organization, its stakeholders, and the society at large“ (Meffert et al., 2024, S. 11).⁶ Das moderne, erweiterte Marketingverständnis integriert die **Beziehungsorientierung** („for managing customer relationships“) als definitorischen Bestandteil und bringt somit den Übergang vom transaktionsorientierten zum beziehungsorientierten Marketing zum Ausdruck (Meffert et al., 2024).

Während Marketing ursprünglich primär auf einzelne Transaktionen ausgerichtet war, richtet sich der Fokus des modernen Marketingverständnisses auf die Gestaltung langfristiger Beziehungen zwischen Anbieter und Nachfrager (Meffert et al., 2024). Da der klassische Marketingansatz primär auf die Bedürfnisbefriedigung durch einmalige Kundentransaktionen ausgerichtet war, wurde vermehrt kritisiert, dass er vernachlässigt, Kunden auch nach dem Kauf an das Unternehmen zu binden und zu Wiederkäufen zu motivieren (Meffert et al., 2024). Aus dieser Kritik an einem rein transaktionsorientierten Marketing entwickelte sich das Konzept des Relationship Marketing (Berry, 1983; Grönroos, 1994; Gummesson, 1994; Payne, 1995; Hennig-Thurau & Hansen, 2000; Kleinaltenkamp et al., 2011).

Das **Relationship Marketing** umfasst „sämtliche Maßnahmen der Analyse, Planung, Durchführung und Kontrolle, die der Initiierung, Stabilisierung, Intensivierung und Wiederaufnahme sowie gegebenenfalls Beendigung von Geschäftsbeziehungen – insbesondere zu

⁶ Die moderne, erweiterte Definition des Marketings nach Meffert et al. (2024) stellt eine Synthese der American Marketing Association (AMA)-Definitionen von 2004 und 2007 dar. Die Version aus dem Jahr 2004 wurde in der Fachliteratur teilweise kritisch beurteilt, da sie als zu eng gefasst gilt – unter anderem, weil sie Organisationen ohne klassische Kundenbeziehungen, wie etwa Wohltätigkeitsorganisationen, nicht berücksichtigt (Hunt, 2010). Diese Kritik löste eine Debatte aus, die schließlich zur Überarbeitung der Definition führte (Hunt, 2010). Die 2007 veröffentlichte Version der AMA-Definition bezieht neben Kunden auch Klienten, Partner sowie die Gesellschaft insgesamt mit ein und spiegelt damit eine breitere Perspektive wider.

den Kunden – des Unternehmens mit dem Ziel des gegenseitigen Nutzens dienen“ (Bruhn, 2022, S. 12). Die zentralen Ziele von Marketingaktivitäten im Rahmen des Relationship Marketing umfassen nicht nur die Kundenakquisition, sondern insbesondere auch die Kundenbindung und Kundenrückgewinnung (Bruhn, 2022).

Die besondere **Relevanz der Kundenbindung** beruht auf der Annahme, dass sie sowohl auf der Erlösseite – beispielsweise durch eine erhöhte Kauffrequenz, Cross-Selling-Potenziale oder eine gesteigerte Preisbereitschaft – als auch auf der Kostenseite – beispielsweise durch Einsparungspotenziale infolge von Erfahrungseffekten – zum ökonomischen Erfolg beiträgt (Reichheld & Sasser, 1990; Blattberg & Deighton, 1996; Zeithaml et al., 1996; Anderson et al., 1997; Hadwich, 2003; Krafft, 2007). Neben diesen **direkten Erfolgswirkungen** hat Kundenbindung durch Mund-zu-Mund-Kommunikation auch eine **indirekte Erfolgswirkung** auf andere Kundenbeziehungen (Bruhn, 2022). Der Mund-zu-Mund-Kommunikation werden indirekte Erfolgswirkungen zugeschrieben, da durch sie ohne direkte Aktivitäten des Anbieters sowohl Kundenabwanderungen vermieden als auch potenzielle Neukunden gewonnen werden können (Bruhn, 2022, S. 4). Abbildung 1 veranschaulicht die **Erfolgswirkungen der Kundenbindung** im Verlauf einer Kundenbeziehung.

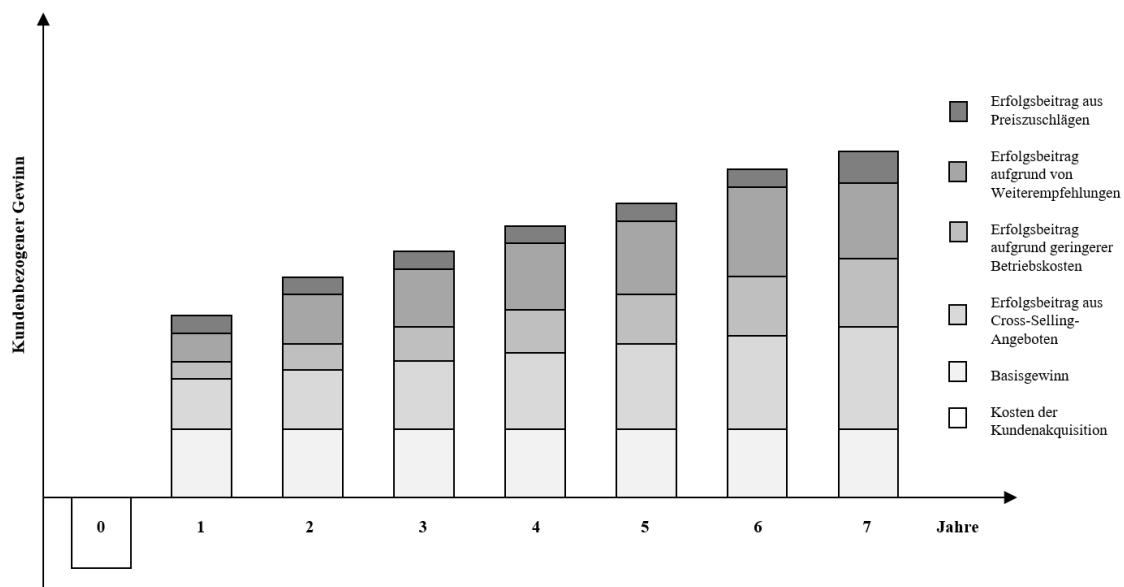


Abbildung 1: Erfolgswirkungen der Kundenbindung im Verlauf einer Kundenbeziehung

Quelle: Eigene Darstellung in Anlehnung an Reichheld und Sasser (1990; 1991, S. 111), Bruhn (2022, S. 5)

Aus dieser Überlegung lässt sich eine grundlegende Konsequenz ableiten: Der Wert eines Kunden bemisst sich nicht länger ausschließlich am Gewinn, der bei einer einzelnen Transaktion erzielt wird. Stattdessen ist das **Gewinnpotenzial über die gesamte Beziehungsdauer** hinweg zu betrachten (Meffert et al., 2024). Wie Abbildung 1 veranschaulicht, steigt das kundenbezogene Gewinnpotenzial tendenziell im zeitlichen Verlauf der Kundenbeziehung. Dieser Zusammenhang wurde von Reichheld und Sasser (1990) anhand von Fallbeispielen aus verschiedenen Branchen aufgezeigt und verdeutlicht, weshalb Unternehmen unter dem Ansatz des Relationship Marketing ein Interesse an langfristigen Kundenbeziehungen und der Vermeidung von Kundenabwanderung haben (Bruhn, 2022; Reichheld & Sasser, 1990).

2.2.2 Die Bedeutung des Kundenwechselerhaltens im Kontext des Relationship Marketing

Erst durch die beziehungsorientierte Perspektive des Relationship Marketing wird die **Relevanz von Kundenabwanderung und Kundenwechselerhalten** deutlich: Falls ein Kunde die Geschäftsbeziehung zu einem Unternehmen frühzeitig beendet, kann das Gewinnpotenzial des Kunden nicht realisiert werden und der kundenbezogene Gewinn fällt gering aus oder ist aufgrund der Kundenakquisitionskosten sogar negativ (Bruhn, 2022; Reichheld & Sasser, 1990). Grundsätzlich gilt: Je niedriger die Kundenabwanderungsrate, desto höher der Unternehmensgewinn (Bruhn, 2022; Reichheld & Sasser, 1990). Reichheld und Sasser (1990) konnten anhand von Fallbeispielen aus verschiedenen Branchen aufzeigen, dass bereits eine Reduktion der Kundenabwanderungsrate um 5 % den Unternehmensgewinn um 25 bis 85 % steigern kann. Ergänzend wiesen Gupta und Lehmann (2003) in ihrer Studie auf Basis öffentlich verfügbarer Finanzdaten anhand von zwei Fallbeispielen nach, dass eine Erhöhung der Kundenbindungsrate um 5 % den Customer-Lifetime-Value um 22 bis 37 % steigern kann. Darüber hinaus zeigte eine Studie von Gupta, Lehmann und Stuart (2004), dass eine Senkung der Kundenakquisitionskosten um 1 % den Unternehmenswert – je nach dem betrachteten Unternehmen – um 0,02 bis 0,32 % steigert, wohingegen eine Erhöhung der Kundenbindungsrate um 1 % zu einer Steigerung des Unternehmenswerts um 2,45 bis 6,75 % führt. Die Elastizität des Unternehmenswertes bezüglich der Kundenbindungsrate ist somit um ein Vielfaches höher als die Elastizität des Unternehmenswertes bezüglich der Kundenakquisitionskosten, wodurch die Relevanz der Vermeidung von Kundenabwanderung gegenüber der Neukundengewinnung

veranschaulicht wird (Gupta et al., 2004). Außerdem zeigten Reinartz, Thomas und Kumar (2005), dass zur Maximierung des Unternehmensgewinns ca. 75 % des Marketingbudgets in Kundenbindungsmaßnahmen und lediglich ca. 25 % in Kundenakquisitionsmaßnahmen investiert werden sollten – eine Verteilung, welche die Bedeutung der Vermeidung von Kundenabwanderung zusätzlich unterstreicht.

Im Rahmen des **Kundenwechselverhaltens** kommt erschwerend hinzu, dass es sich um ein **zweiseitiges Phänomen** handelt: Während ein Unternehmen einen Kunden und damit verbundenes Gewinnpotenzial verliert, gewinnt ein Wettbewerber diesen Kunden, wodurch die Wettbewerbsposition des verlierenden Unternehmens zusätzlich geschwächt wird (Marx, 2025).

2.3 Digitale Dienstleistungen

2.3.1 Besonderheiten digitaler Dienstleistungen

Dienstleistungen (engl. services) sind „selbstständige, marktfähige Leistungen, die mit der Bereitstellung (z. B. Versicherungsleistungen) und/oder dem Einsatz von Leistungsfähigkeiten (z. B. Friseurleistungen) verbunden sind (Potenzialorientierung). Interne (z. B. Geschäftsräume, Personal, Ausstattung) und externe Faktoren (also solche, die nicht im Einflussbereich des Dienstleisters liegen) werden im Rahmen des Erstellungsprozesses kombiniert (Prozessorientierung). Die Faktorenkombination des Dienstleistungsanbieters wird mit dem Ziel eingesetzt, an den externen Faktoren, an Menschen (z. B. Kunden) und deren Objekten (z. B. Auto des Kunden) nutzenstiftende Wirkungen (z. B. Inspektion beim Auto) zu erzielen (Ergebnisorientierung)“ (Meffert et al., 2018, S. 15).

Gemäß Meffert et al. (2018) weisen Dienstleistungen in Abgrenzung zu Produkten⁷ **drei grundlegende Besonderheiten** auf: Die erste Besonderheit ist die **Notwendigkeit der Leistungsfähigkeit des Dienstleistungsanbieters**. Damit ist gemeint, dass die Erstellung einer Dienstleistung nur dann möglich ist, wenn der Dienstleistungsanbieter über spezifische

⁷ Es ist darauf hinzuweisen, dass einige Autoren zu dem Ergebnis kommen, dass eine exakte Trennung zwischen Produkten und Dienstleistungen nicht immer möglich ist (Meffert et al., 2018; Schmidt, 2007; Stelzer, 2000). Dies liegt unter anderem daran, dass viele Produkte mit einem gewissen Dienstleistungsanteil verbunden sind – etwa im Fall erklärungsbedürftiger Gebrauchsgüter (Meffert et al., 2018). Manche Autoren gehen noch weiter und erachten die Unterscheidung zwischen Produkten und Dienstleistungen als grundsätzlich fehlgeleitet, weil aus ihrer Sicht sämtliche wirtschaftlichen Aktivitäten im Kern aus Dienstleistungen im Sinne eines Austauschs spezialisierter Fähigkeiten bestehen und Produkte lediglich als Distributionsmechanismen zur Bereitstellung dieser Dienstleistungen fungieren (Vargo & Lusch, 2004a).

Leistungsfähigkeiten (z. B. Know-how, körperliche Fähigkeiten, Technologie oder personelle Ressourcen) verfügt (Meffert et al., 2018). Die zweite Besonderheit besteht darin, dass die **Integration eines externen Faktors**, d. h. die Einbeziehung des Dienstleistungsnachfragers oder eines ihm gehörenden Objekts, zwingend notwendig ist (Meffert et al., 2018). Die dritte Besonderheit ist die **Immaterialität des Leistungsergebnisses**. Obwohl bei der Erbringung der Dienstleistung eine physische Veränderung des Fremdfaktors stattfinden kann (z. B. Autowaschanlage), besteht das Ziel des Dienstleistungsanbieters nicht in der Herstellung eines physischen Objekts (Knoblich & Oppermann, 1996; Meffert et al., 2018).

Neben diesen drei grundlegenden Besonderheiten weisen digitale Dienstleistungen **spezifische Besonderheiten** auf (Urbach, 2016). Bevor diese dargelegt werden, bedarf es jedoch zunächst einer begrifflichen Einordnung. **Digitale Dienstleistungen** (engl. digital services) lassen sich – in Anlehnung an die Definition digitaler Güter von Clement et al. (2019) – als Dienstleistungen bezeichnen, „die aus Binärdaten (0, 1) bestehen und sich mit Hilfe von Informations- und Kommunikationstechnologien entwickeln, vertreiben oder anwenden lassen“ (Clement et al., 2019, S. 34). Der **Digitalisierungsgrad** einer Dienstleistung lässt sich anhand der drei der Definition zugrundeliegenden Dimensionen – Produktion, Vertrieb und Anwendung – differenzieren (Choi et al., 1997; Clement et al., 2019; Urbach, 2016). Eine **rein digitale Dienstleistung** wird demnach sowohl digital produziert als auch vertrieben und angewendet. Ein Beispiel hierfür ist das Online-Banking via Smartphone-App. Die Smartphone-App wird von dem Dienstleistungsanbieter programmiert, d. h. digital produziert, per Download in einem App-Store vertrieben und schließlich auf einem digitalen Endgerät – dem Smartphone – von dem Dienstleistungsnachfrager genutzt. Eine **rein physische Dienstleistung** wird hingegen physisch produziert, vertrieben und angewendet. Ein Beispiel dafür ist ein Friseurbesuch. Zwischen rein digitalen und rein physischen Dienstleistungen existieren diverse **Mischformen**. Ein Beispiel für eine solche Mischform ist Click-and-Collect im Einzelhandel. Die Produktion erfolgt physisch, indem die Waren in der Filiale von Mitarbeitenden des Einzelhändlers kommissioniert werden. Der Vertrieb geschieht digital, indem der Dienstleistungsnachfrager die gewünschten Produkte online per Smartphone-App auswählt und bezahlt. Die Anwendung ist schließlich wieder physisch, da die Ware vom Dienstleistungsnachfrager vor Ort abgeholt wird. Die weiteren Ausführungen in diesem Kapitel beziehen sich insbesondere auf rein digitale Dienstleistungen.

Die erste spezifische Besonderheit rein digitaler Dienstleistungen besteht in ihrer **eingeschränkten Wahrnehmbarkeit** (Urbach, 2016). Während rein physische Dienstleistungen wie etwa ein Restaurantbesuch grundsätzlich über alle fünf menschlichen Sinne – Sehen, Hören, Riechen, Schmecken und Tasten – wahrgenommen und bewertet werden können, beschränkt sich die Wahrnehmung rein digitaler Dienstleistungen auf lediglich zwei Sinne: Sehen und Hören (Urbach, 2016). Die fehlende physische Wahrnehmbarkeit kann die Vergleichbarkeit erschweren und zu Marktunsicherheit sowie erhöhten Informationskosten führen (Schmidt, 2007; Urbach, 2016).

Die zweite spezifische Besonderheit rein digitaler Dienstleistungen besteht in ihrer **konstanten Qualität** (Clement et al., 2019; Urbach, 2016). Während die Qualität rein physischer Dienstleistungen im Zeitverlauf schwanken kann, beispielsweise, weil Restaurantpersonal zu Beginn einer Schicht möglicherweise freundlicher und aufmerksamer ist als am Ende, bleibt die Qualität digitaler Dienstleistungen grundsätzlich konstant (Seidenfaden & Hagenhoff, 2004; Urbach, 2016). So hängt beispielsweise die Qualität der Antwort eines Chatbots weder von der Tageszeit noch vom aktuellen Auslastungsgrad ab.⁸

Die dritte spezifische Besonderheit rein digitaler Dienstleistungen besteht in ihrer **einfachen Reproduzierbarkeit** (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Da rein digitale Dienstleistungen aus Binärdaten bestehen, können sie grundsätzlich mit geringem technischem Aufwand reproduziert werden (Clement et al., 2019). So lässt sich beispielsweise eine App zum Erlernen von Fremdsprachen bei Zugriff auf die entsprechenden Dateien relativ leicht kopieren. Ein Präsenzsprachkurs hingegen ist nicht kopierbar, da seine Erbringung an Ort, Zeit und personellen Einsatz gebunden ist. Anbietern rein digitaler Dienstleistungen kann es daher schwerfallen, die unbefugte Weitergabe an Dritte wirksam zu unterbinden (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016).

Die vierte und letzte Besonderheit rein digitaler Dienstleistungen besteht in ihrer **einfachen Veränderbarkeit** (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Rein digitale Dienstleistungen lassen sich mit geringem Aufwand modifizieren, sodass Anbieter sie bei Bedarf aktualisieren oder personalisieren können (Urbach, 2016). So kann eine App zum Erlernen von Fremdsprachen beispielsweise an die Vorkenntnisse und Präferenzen einzelner Nutzer angepasst

⁸ Es sei angemerkt, dass die Ausführungen zur konstanten Qualität digitaler Dienstleistungen nur unter der Voraussetzung einer stabilen technischen Infrastruktur gelten.

werden, während dies in einem Präsenzsprachkurs mit mehreren Teilnehmenden nicht ohne Weiteres möglich ist. Gleichzeitig erhöht diese einfache Veränderbarkeit jedoch auch das Risiko unbefugter Manipulation, etwa durch Hacks oder Schadsoftware (Urbach, 2016).

2.3.2 Betriebswirtschaftliche Besonderheiten digitaler Dienstleistungen

Die zuvor dargelegten Charakteristika digitaler Dienstleistungen führen aus betriebswirtschaftlicher Perspektive zu verschiedenen Besonderheiten (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016), die im Folgenden näher erläutert werden.

Die erste betriebswirtschaftliche Besonderheit rein digitaler Dienstleistungen besteht in ihrer **Kostenstruktur** (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Rein digitale Dienstleistungen sind in der Regel durch eine Kostenstruktur gekennzeichnet, die aus hohen Fixkosten für Entwicklung und Erstproduktion, den sogenannten First-Copy-Costs, sowie im Vergleich dazu vernachlässigbar geringen variablen Kosten für Reproduktion und Vertrieb besteht (Bakos & Brynjolfsson, 2000; Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Erweisen sich die relativ hohen Entwicklungskosten im Nachhinein als nicht verwertbar, liegen versunkene Kosten vor (Clement et al., 2019). Grundsätzlich sinken die Fixkosten pro produzierter Einheit mit zunehmender Ausbringungsmenge – ein Effekt, der als Fixkostendegression bzw. Stückkostendegression bezeichnet wird (Clement et al., 2019). Je geringer dabei die variablen Kosten im Verhältnis zu den Fixkosten ausfallen, desto stärker wirkt dieser Effekt (Clement et al., 2019). Für Anbieter rein digitaler Dienstleistungen ist es daher besonders attraktiv, die Ausbringungsmenge möglichst stark auszudehnen (Clement et al., 2019; Urbach, 2016).

Die zweite betriebswirtschaftliche Besonderheit rein digitaler Dienstleistungen besteht in **positiven Feedback-Effekten** (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Hintergrund ist die zuvor beschriebene charakteristische Kostenstruktur, die es dem Anbieter mit dem größten Marktanteil ermöglicht, durch Fixkostendegression seine Stückkosten schneller zu senken als die Wettbewerber (Clement et al., 2019). Dadurch kann er höhere Gewinne realisieren oder seine Preise schneller senken, was ihm ceteris paribus wiederum einen weiteren Ausbau seines Marktanteils ermöglicht (Clement et al., 2019; Urbach, 2016). Diese sich selbst verstärkenden Wirkungen werden als positive Feedback-Effekte bezeichnet (Clement et al., 2019; Shapiro & Varian, 1998). Sie können dazu führen, dass ein Markt von wenigen Anbietern dominiert wird,

während neue Anbieter es vergleichsweise schwer haben, sich am Markt zu etablieren (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016).

Die dritte betriebswirtschaftliche Besonderheit rein digitaler Dienstleistungen besteht im **Systemwettbewerb** (Shapiro & Varian, 1998; Urbach, 2016). Im digitalen Kontext stehen oft nicht einzelne Dienstleistungen isoliert im Wettbewerb, sondern Bündel komplementärer und miteinander verbundener Dienstleistungen (Shapiro & Varian, 1998; Stelzer, 2000; Urbach, 2016). Ein Beispiel ist eine Online-Banking-App, die neben den Kerndienstleistungen – etwa der Abfrage des Kontostands sowie dem Tätigen von Überweisungen – auch zusätzliche Dienstleistungen wie Wertpapierhandel, Kreditaufnahme oder die Geldautomatensuche umfasst.

Die vierte betriebswirtschaftliche Besonderheit rein digitaler Dienstleistungen besteht in **Netzwerkeffekten** (Shapiro & Varian, 1998; Urbach, 2016). Netzwerkeffekte treten auf, wenn der Nutzen einer Dienstleistung für einzelne Nutzer davon abhängt, wie viele andere diese Dienstleistung ebenfalls nutzen (Shapiro & Varian, 1998). Ein Beispiel ist der Markt für Suchmaschinen: Je mehr Nutzer eine bestimmte Suchmaschine verwenden, desto größer wird die Datenbasis, anhand derer die Suchergebnisse optimiert werden können (Klein et al., 2025). Dadurch steigt die Relevanz der Ergebnisse für alle Nutzer (Klein et al., 2025). Gleichzeitig wird die Suchmaschine für werbetreibende Unternehmen attraktiver, wodurch der Anbieter der Suchmaschine zusätzliche Werbeeinnahmen generieren kann (Klein et al., 2025). Netzwerkeffekte können somit dazu führen, dass sich einzelne Anbieter am Markt durchsetzen und Wettbewerber verdrängen (Shapiro & Varian, 1998; Urbach, 2016).

Die fünfte betriebswirtschaftliche Besonderheit rein digitaler Dienstleistungen besteht gemäß Urbach (2016) in **datenbasierter Nutzungspfadabhängigkeit** (auch als Lock-in-Effekt bezeichnet, vgl. z. B. Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Digitale Dienstleistungen lassen sich aufgrund ihrer leichten Veränderbarkeit gezielt an individuelle Konsumpräferenzen anpassen (Clement et al., 2019; Urbach, 2016). Ein Anbieterwechsel ist für Konsumenten daher nicht nur mit dem Aufwand der Neueinrichtung verbunden (Shapiro & Varian, 1998), sondern auch mit dem Verlust zuvor gesammelter Nutzungsdaten und darauf basierender Funktionen (Urbach, 2016). So erfasst beispielsweise ein Musik-Streamingdienst im Zeitverlauf die musikalischen Vorlieben seiner Nutzer und nutzt diese Informationen, um personalisierte Empfehlungen bereitzustellen (Dörr et al., 2010). Wechselt der Nutzer zu einem anderen Musik-

Streamingdienst, muss dieser die Präferenzen zunächst erneut erlernen – was kurzfristig zu einem weniger passgenauen Nutzungserlebnis führt (Schedl et al., 2018). Solche datenbasierten Nutzungspfadabhängigkeiten können die Bereitschaft zum Anbieterwechsel im digitalen Dienstleistungskontext verringern (Urbach, 2016).

2.3.3 Konsequenzen für das Kundenwechselverhalten im Kontext digitaler Dienstleistungen

Das Kundenwechselverhalten im Kontext digitaler Dienstleistungen wird maßgeblich durch die zuvor beschriebenen betriebswirtschaftlichen Besonderheiten beeinflusst (Urbach, 2016). Zunächst ist festzuhalten, dass aufgrund der charakteristischen **Kostenstruktur** digitaler Dienstleistungen die Grenzkosten nahezu null betragen (Clement et al., 2019). Unter den Annahmen eines Bertrand-Preiswettbewerbs im Oligopol würde dies dazu führen, dass digitale Dienstleistungen kostenfrei angeboten werden (Clement et al., 2019; Peters, 2010). Um einem solchen Preiswettbewerb zu entgehen, setzen Anbieter digitaler Dienstleistungen häufig auf **indirekte Erlösmodelle**, bei denen die Nutzung zunächst kostenlos ermöglicht wird und die Erlöse erst während der Inanspruchnahme generiert werden (Clement et al., 2019; Seidenfaden & Hagenhoff, 2004; Urbach, 2016). Zu den zentralen Formen indirekter Erlösmodelle zählen die Finanzierung durch Werbung, Provisionen und Sponsorship sowie die Verarbeitung oder der Verkauf von Nutzerdaten (Clement et al., 2019; Urbach, 2016; Wirtz, 2024). Besonders ausgeprägt ist die Anwendung solcher Modelle in Branchen wie sozialen Medien, Suchmaschinen oder Webbrowsern (Clement et al., 2019). Mit der wachsenden Bedeutung von KI gewinnt insbesondere das Modell des zunächst kostenlosen Angebots, das auf eine schnelle und umfassende Verarbeitung von Nutzerdaten abzielt, zusätzlich an Relevanz, da größere Datenmengen ceteris paribus die Entwicklung leistungsfähigerer KI-Modelle ermöglichen (Harari, 2024). Die weite Verbreitung indirekter Erlösmodelle im digitalen Dienstleistungskontext begünstigt grundsätzlich Kundenwechselverhalten, da der Preis als zentrale Wechselbarriere an Bedeutung verliert (Pick, 2016). Sie führt zudem häufig zu einer parallelen Nutzung mehrerer Angebote, wodurch das teilweise Kundenwechselverhalten als Untersuchungsgegenstand besonders in den Fokus rückt (Ye & Potter, 2011).

Neben der Kostenstruktur wirken sich jedoch auch die anderen betriebswirtschaftlichen Besonderheiten digitaler Dienstleistungen auf das Kundenwechselverhalten aus. **Positive**

Feedback-Effekte ermöglichen es Anbietern mit großem Marktanteil, Fixkostendegression schneller zu realisieren und ihre Wettbewerbsposition durch Gewinnrealisierung oder Preisreduktionen auszubauen (Clement et al., 2019; Urbach, 2016). Diese selbst verstärkenden Effekte führen häufig zu hoher Marktkonzentration, wodurch neue Anbieter vor erheblichen Markteintrittsbarrieren stehen (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Darüber hinaus treten Anbieter im **Systemwettbewerb** nicht mit einzelnen Dienstleistungen, sondern mit Bündeln komplementärer Angebote gegeneinander an (Shapiro & Varian, 1998; Stelzer, 2000; Urbach, 2016). Ein Wechsel erfordert daher oft den Verzicht auf komplementäre Funktionen oder die Umstellung auf ein alternatives, weniger vertrautes Bündel, was die Wechselkosten erhöhen kann (Shapiro & Varian, 1998; Urbach, 2016).⁹ Auch **Netzwerkeffekte** verstärken die Dominanz einzelner Anbieter, da der Nutzen einer digitalen Dienstleistung mit der Zahl ihrer Nutzer steigt (Shapiro & Varian, 1998; Urbach, 2016). Größere Nutzerzahlen verbessern beispielsweise die Relevanz von Suchergebnissen, was die Attraktivität des führenden Suchmaschinenanbieters zusätzlich erhöht (Klein et al., 2025). Schließlich wirken **datenbasierte Nutzungspfadabhängigkeiten** kundenbindend (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Durch die fortlaufende Anpassung der digitalen Dienstleistung an individuelle Präferenzen wird ein Wechsel unattraktiv, da gesammelte Nutzungsdaten und darauf basierende personalisierte Funktionen beim Anbieterwechsel in der Regel verloren gehen (Clement et al., 2019; Dörr et al., 2010; Schedl et al., 2018; Urbach, 2016).

Zusammenfassend begünstigt die Kostenstruktur digitaler Dienstleistungen durch die weite Verbreitung indirekter Erlösmodelle grundsätzlich Kundenwechselverhalten, da der Preis als zentrale Wechselbarriere an Bedeutung verliert und eine parallele Nutzung mehrerer Angebote erleichtert wird (Clement et al., 2019; Pick, 2016; Shapiro & Varian, 1998; Urbach, 2016; Ye & Potter, 2011). Im Gegensatz dazu machen die übrigen betriebswirtschaftlichen Besonderheiten – positive Feedback-Effekte, Systemwettbewerb, Netzwerkeffekte und datenbasierte Nutzungspfadabhängigkeiten – Kundenwechselverhalten tendenziell unattraktiver und tragen zugleich zu einer hohen Marktkonzentration bei, welche die real verfügbaren Wechseloptionen langfristig deutlich einschränkt (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016).

⁹ Interoperabilität kann die mit einem Wechsel verbundenen Nachteile reduzieren, da sie die Weiternutzung komplementärer Funktionen ermöglicht und den Umstellungsaufwand begrenzt, was zu niedrigeren Wechselkosten führt (Farrell & Klemperer, 2007; Shapiro & Varian, 1998).

2.4 Theoretische Ansätze zur Erklärung des Kundenwechselverhaltens

„There is nothing so practical as a good theory“ – dieser vielzitierte Satz von Kurt Lewin (1951, S. 169) bringt die Bedeutung von **Theorien**¹⁰ treffend auf den Punkt, insbesondere vor dem Hintergrund, dass Theorien von Praktikern häufig fälschlicherweise als zu abstrakt und wenig hilfreich beurteilt werden (Kuß, 2013). Gerade angesichts zunehmender Datenverfügbarkeit bewährt sich die Aussage von Kurt Lewin: Wie Gröppel-Klein und Kroeber-Riel (2025, S. 7) betonen, ermöglichen gut begründete Annahmen über Ursache-Wirkungs-Zusammenhänge, „die Daten-Spreu vom Daten-Weizen zu trennen“ und Scheinkorrelationen aufzudecken.

Die eigenständige Auseinandersetzung mit theoretischen Ansätzen zur Erklärung von Kundenwechselverhalten ist notwendig, da die Einflussfaktoren, die zu positiven Ergebnissen wie Kundenloyalität führen, nicht zwangsläufig identisch mit jenen sind, die negative Ergebnisse wie Kundenwechselverhalten verursachen (Bansal & Taylor, 1999; Keaveney, 1995).¹¹ Obgleich das Other-Side-of-the-Coin-Argument¹² grundsätzlich berechtigt ist und bestimmte Variablen wie Kundenzufriedenheit sowohl Kundenloyalität als auch Kundenwechselverhalten beeinflussen können (Antón et al., 2007a), reicht es nicht aus, etablierte Theorien zur Erklärung positiver Ergebnisse wie die Commitment-Trust-Theorie (Morgan & Hunt, 1994) oder das Servqual-Modell (Parasuraman et al., 1988), die häufig zur Erklärung von Kundenloyalität herangezogen werden (vgl. z. B. Alcántara-Pilar et al., 2024; Ly, 2025; Setó-Pamies, 2012), schlicht auf das Kundenwechselverhalten zu übertragen, indem lediglich die abhängige Variable ausgetauscht

¹⁰ Eine Theorie wird im Rahmen dieser Arbeit definiert als „eine Menge von Aussagen über die Beziehung(en) zwischen zwei oder mehr Konzepten bzw. Konstrukten“ (Jaccard & Jacoby, 2010, S. 28). Da es deutliche Überschneidungen zwischen dem Theorie-Begriff und dem Modell-Begriff gibt (Kuß, 2013), sei an dieser Stelle kurz auf die Abgrenzung eingegangen. Ein Modell bezeichnet eine „vereinfachte Darstellung relevanter Teile der Realität“ (Kuß, 2013, S. 55). Dabei lassen sich verschiedene Modellarten unterscheiden, etwa grafische (z. B. Landkarte), gegenständliche (z. B. Holzmodell eines Gebäudes), verbale (z. B. Beschreibung von Zusammenhängen) sowie mathematische Modelle (z. B. Regressionsmodell) (Kuß, 2013). Theorien stellen in diesem Sinne eine spezielle Form von Modellen dar – in der Marketingforschung handelt es sich dabei in der Regel um verbale Modelle (Kuß, 2013). Entsprechend können Theorien als Teilmenge von Modellen aufgefasst werden, d. h., jede Theorie ist ein Modell, jedoch ist nicht jedes Modell auch eine Theorie (Kuß, 2013). Darüber hinaus sei darauf hingewiesen, dass die Bezeichnung von Theorien und Modellen in der Literatur nicht immer der hier dargelegten, präzisen Unterscheidung folgt: So führt Kuß (2013) beispielsweise das Elaboration-Likelihood-Modell (Petty et al., 1983) als Beispiel für eine Theorie an.

¹¹ Es sei angemerkt, dass die Bewertung von Kundenloyalität als „positiv“ bzw. von Kundenwechselverhalten als „negativ“ jeweils nur unter der Annahme zutrifft, dass es sich um profitable Kunden handelt.

¹² Das Other-Side-of-the-Coin-Argument bezeichnet in diesem Zusammenhang die Annahme, dass sich Kundenloyalität und Kundenwechselverhalten als zwei Seiten derselben Medaille verstehen lassen, sodass die Faktoren, die Loyalität fördern, umgekehrt auch Wechselverhalten verhindern sollten (Antón et al., 2007a).

wird. Vielmehr erfordert die Erklärung von Kundenwechselverhalten **eigene theoretische Ansätze**. Dies gilt insbesondere auch deshalb, weil es sich beim Kundenwechselverhalten – anders als bei Kundenloyalität – um ein zweiseitiges Phänomen handelt, bei dem, wie zuvor beschrieben, der Status-quo und eine Alternative miteinander verglichen werden (Marx, 2025).

Ein Literaturüberblick zu Kundenwechselverhalten im Dienstleistungskontext von Chuang und Tai (2016) bezeichnet die Studie von Keaveney (1995) als wegbereitend für die nachfolgende Theoretisierung, da in dieser das Kundenwechselverhalten erstmals explizit untersucht wurde. Auf Grundlage von 516 Interviews wurden dabei die Gründe für Kundenwechselverhalten qualitativ erfasst (Keaveney, 1995). Aufbauend auf der Studie von Keaveney (1995) setzte in der Folge eine Phase der Modellformulierung ein, in der versucht wurde, die identifizierten Wechselgründe in empirisch-quantitativ prüfbare Modelle zu überführen sowie weitere relevante Determinanten zu identifizieren (Chuang & Tai, 2016). Diese Phase mündete in vier unterschiedliche Modelle zur Erklärung von Kundenwechselverhalten, die in Tabelle 2 dargestellt sind (Chuang & Tai, 2016).

Erwähnenswert sind in diesem Zusammenhang auch die Studien von Antón et al. (2007a; 2007b), die von Chuang und Tai (2016) ebenfalls im Rahmen der Modellformulierung aufgeführt werden. In Tabelle 2 bleiben sie jedoch unberücksichtigt, da sie keinen Anspruch erheben, ein explizit benanntes Modell zur Erklärung von Kundenwechselverhalten zu formulieren, das in nachfolgenden Studien aufgegriffen werden könnte.

Autoren (Jahr)	Titel	Modell	Varianzaufklärung	Zitationen ¹³	Anwendungen ¹⁴
Bansal, H. S., & Taylor, S. F. (1999)	The service provider switching model (SPSM): A model of consumer switching behavior in the services industry	Service Provider Switching Model	Wechselintention: 76 % Wechselverhalten: 30 %	902	1
Bansal, H. S., & Taylor, S. F. (2002)	Investigating interactive effects in the theory of planned behavior in a service-provider switching context	Theory of Planned Behavior	Wechselintention: 79 % Wechselverhalten: 31 %	429	76
Bansal, H. S., Irving, P. G., & Taylor, S. F. (2004)	A three-component model of customer commitment to service providers	Three-Component Model of Customer Commitment	Wechselintention: 29 %	1802	1
Bansal, H. S., Taylor, S. F., & St. James, Y. (2005)	“Migrating” to new service providers: Toward a unifying framework of consumers’ switching behaviors	Push-Pull-Mooring Model	Wechselintention: 68 % Wechselverhalten: 57 %	1552	202

Tabelle 2: Modelle zur Erklärung von Kundenwechselverhalten im Vergleich

Quelle: Eigene Darstellung

¹³ Zitationszahlen gemäß Google Scholar (Stand: 29.10.2025)

¹⁴ Die Anwendungszahlen basieren auf einer Scopus-Recherche (Stand: 29.10.2025) mit den folgenden Suchsträngen: TITLE-ABS-KEY (“service provider switching model”) AND TITLE-ABS-KEY (“switching”), TITLE-ABS-KEY (“theory of planned behavior”) AND TITLE-ABS-KEY (“switching”), TITLE-ABS-KEY (“three component model of customer commitment”) AND TITLE-ABS-KEY (“switching”), TITLE-ABS-KEY (“push pull mooring model”) OR “push pull mooring theory” OR “push pull mooring framework”) AND TITLE-ABS-KEY (“switching”)

Obgleich die in Tabelle 2 dargestellten Anwendungszahlen nicht sämtliche existierende Studien zu den jeweiligen Modellen abdecken mögen, bieten sie eine hinreichende Grundlage für die folgende Argumentation: Weder das **Three-Component Model of Customer Commitment (TCMCC)** noch das **Service Provider Switching Model (SPSM)** haben sich in der Forschung zum Kundenwechselerhalten durchgesetzt. Breitere Anwendung finden lediglich die **Theory of Planned Behavior (TPB)** sowie das **Push-Pull-Mooring (PPM)-Modell**, wobei sich Letzteres als das am häufigsten eingesetzte Modell etabliert hat (Tabelle 2).

Für diese Entwicklung lassen sich mehrere Gründe anführen: Die TPB verfolgt einen generalistischen Erklärungsansatz für menschliches Verhalten – so nennt Ajzen (1991) etwa Verhaltensbereiche wie die Jobsuche, Gewichtsreduktion oder Wahlbeteiligung als Anwendungsfelder. Im Gegensatz dazu sind das SPSM, das TCMCC und das PPM-Modell spezifisch auf die Erklärung und Vorhersage von Wechselintentionen bzw. Wechselverhalten ausgerichtet und weisen damit einen enger gefassten intendierten Anwendungsbereich¹⁵ auf (Bansal & Taylor, 1999; Bansal et al., 2004; Bansal et al., 2005). Innerhalb dieser spezialisierten Modelle zeigt sich jedoch deutlich, dass sich das PPM-Modell in der empirischen Forschung durchgesetzt hat (Tabelle 2) – obwohl es im Vergleich nicht die höchste Varianzaufklärung der Wechselintention bietet, wobei jedoch anzumerken ist, dass es sich bei den in Tabelle 2 aufgeführten Zahlen zur Varianzaufklärung um empirische Evidenz aus den jeweils einzelnen Studien handelt und nicht etwa um meta-analytisch aggregierte Evidenz, sodass die Aussagekraft dieses Vergleichs begrenzt ist. Dies lässt sich wie folgt erklären: Das SPSM leitet seine unabhängigen Variablen zwar aus bestehender Literatur zum Kundenwechselerhalten und der TPB ab, bleibt in der konkreten Auswahl jedoch weitgehend arbiträr (Bansal & Taylor, 1999). Es fehlt eine klare theoretische Rahmung. Das TCMCC konzentriert sich ausschließlich auf eine einzelne Determinante, nämlich Commitment, das in eine affektive, eine normative und eine kalkulatorische Dimension unterteilt wird (Bansal et al., 2004). Dadurch ist der Erklärungsbeitrag zur Wechselintention insgesamt begrenzt. Die vor dem PPM-Modell entwickelten Erklärungsansätze zum Kundenwechselerhalten werden von Bansal et al. (2005) retrospektiv selbst als begrenzte Versuche eingestuft. Die Autoren halten fest, dass „at present, marketing literature lacks comprehensive models for service provider switching“ (Bansal et al., 2005, S. 97).

¹⁵ Der intendierte Anwendungsbereich bezeichnet die pragmatisch festgelegte, jedoch prinzipiell erweiterbare Menge von Fällen, auf die eine Theorie sinnvoll angewendet werden kann (Stegmüller, 1980; Ott, 1998).

Im Gegensatz dazu bietet das PPM-Modell, adaptiert aus der Migrationsforschung, erstmals ein theoretisch fundiertes Rahmenwerk (Bansal et al., 2005). Es ermöglicht eine systematische Kategorisierung relevanter Variablen in drei Faktoren: den **Push-Faktor**, der negative Einflüsse am Herkunftsort beschreibt und dadurch abstoßend wirkt (Stimson & Minnery, 1998), den **Pull-Faktor**, der positive Einflüsse am Zielort darstellt und somit anziehend wirkt (Moon, 1995), sowie den **Mooring-Faktor**, der persönliche oder soziale Einflüsse umfasst und eine Migration entweder erschweren oder erleichtern kann (Longino, 1992; Moon, 1995). Dabei kann der Mooring-Faktor die Zusammenhänge zwischen Push- und Pull-Faktoren und der Migrationsentscheidung moderieren, indem er die positiven Einflüsse von Push- und Pull-Faktoren abschwächt (Lee, 1966). Übertragen auf den Dienstleistungskontext ist die Analogie unmittelbar ersichtlich: Kunden (Migranten) wechseln (ziehen um) von einer Dienstleistung (Ort) zu einer anderen. Bansal et al. (2005) bezeichnen das PPM-Modell dementsprechend als ein vereinheitlichendes Rahmenwerk zur Erklärung von Kundenwechselverhalten im Dienstleistungskontext.

Gemäß dem Literaturüberblick zu Kundenwechselverhalten im Dienstleistungskontext von Chuang und Tai (2016) befindet sich die Forschung zum Kundenwechselverhalten nun seit dem Jahr 2007 in einer Phase der Modellprüfung, in der die zuvor entwickelten Modelle – in dem zuvor skizzierten, unterschiedlich starken Ausmaß – in verschiedenen Anwendungskontexten empirisch getestet werden (vgl. z. B. Marx, 2025).

3 Systematische Einordnung der Beiträge

Im vorangegangenen Kapitel wurden die begrifflichen und theoretischen Grundlagen der vorliegenden Arbeit dargestellt. Darauf aufbauend erfolgt nun die systematische Einordnung der ausgewählten Beiträge. Zu diesem Zweck werden die Beiträge zunächst inhaltlich kurz zusammengefasst und im Anschluss systematisiert, um Gemeinsamkeiten, Unterschiede und Schwerpunkte zu verdeutlichen.

Der **Beitrag 1** mit dem Titel „**The push-pull-mooring model of service switching: A meta-analysis**“ wurde im Jahr 2023 in den *Advances in Consumer Research* veröffentlicht und liefert erstmalig meta-analytische Evidenz zum PPM-Modell im Dienstleistungskontext. Das Ziel des Beitrags ist es, eine erste umfassende Übersicht über die Anwendung des PPM-Modells in der bisherigen Forschung zu geben und die Effekte der zentralen Prädiktoren auf das Konsumentenwechselverhalten meta-analytisch zu untersuchen.

Im ersten Schritt wird basierend auf 131 empirisch-quantitativen Studien analysiert, welche Variablen in der bisherigen Forschung am häufigsten zur Erklärung des Konsumentenwechselverhaltens im Dienstleistungskontext verwendet wurden und wie diese jeweils als Push-, Pull-, und Mooring-Variablen kategorisiert wurden. Anschließend werden die Effekte der drei am häufigsten genutzten und einzigen eindeutig kategorisierbaren Variablen – Unzufriedenheit (Push), Attraktivität der Alternative (Pull) und Wechselkosten (Mooring) – auf die Wechselintention und das tatsächliche Wechselverhalten untersucht. Die Ergebnisse der meta-analytischen Strukturgleichungsmodellierung zeigen, dass Unzufriedenheit und Attraktivität der Alternative die Wechselintention erhöhen, während Wechselkosten diese verringern. Die Wechselintention wirkt sich wiederum positiv auf das tatsächliche Wechselverhalten aus.

Mit dieser ersten Meta-Analyse zum PPM-Modell im Dienstleistungskontext wird ein bedeutsamer Beitrag zur Strukturierung der bisher fragmentierten Forschung geleistet. Sie legt die Grundlage für eine vertiefte Auseinandersetzung mit dem PPM-Modell und dient als Ausgangspunkt für weiterführende Analysen.

Der **Beitrag 2** mit dem Titel „**The push-pull-mooring model of consumer service switching: A meta-analytical review to guide future research**“ stellt eine Weiterentwicklung von Beitrag 1 dar und wurde im Jahr 2025 im *Journal of Service Theory and Practice* publiziert. Im Vergleich

zu Beitrag 1 wird die Anzahl der berücksichtigten Studien erweitert, um den aktuellen Forschungsstand möglichst vollständig abzubilden. Darüber hinaus werden die in den Studien verwendeten Messinstrumente systematisch analysiert, und es wird eine meta-analytische Moderationsanalyse durchgeführt.

Basierend auf 148 empirisch-quantitativen Studien wird analysiert, welche Variablen in der bisherigen Forschung am häufigsten zur Erklärung des Konsumentenwechselverhaltens im Dienstleistungskontext verwendet wurden, wie diese jeweils als Push-, Pull-, und Mooring-Variablen kategorisiert und mithilfe welcher Messinstrumente sie operationalisiert wurden. Die Ergebnisse zeigen, dass insgesamt 382 verschiedene unabhängige Variablen genutzt wurden, wobei Unzufriedenheit (Push), Attraktivität der Alternative (Pull) und Wechselkosten (Mooring) die drei am häufigsten genutzten und einzigen eindeutig kategorisierbaren Variablen sind. Darüber hinaus zeigen die Ergebnisse eine erhebliche Heterogenität der Messinstrumente: Insgesamt wurden 152 unterschiedliche Skalen zur Messung von Unzufriedenheit, Attraktivität der Alternative, Wechselkosten, Wechselintention und Wechselverhalten eingesetzt. Die Ergebnisse der meta-analytischen Strukturgleichungsmodellierung bestätigen die bereits in Beitrag 1 identifizierten Effekte: Unzufriedenheit und Attraktivität der Alternative erhöhen die Wechselintention, während Wechselkosten diese verringern. Die Wechselintention hat wiederum einen positiven Einfluss auf das tatsächliche Wechselverhalten. Die anschließend durchgeführte Moderationsanalyse zeigt, dass bestimmte studienspezifische Faktoren – wie die Art des Wechsels (Technologie- vs. Anbieterwechsel) und die Art der Wechselkosten (monetär vs. nicht-monetär) – die identifizierten Effekte beeinflussen.

Aufbauend auf den Ergebnissen werden konkrete Empfehlungen für die zukünftige Anwendung des PPM-Modells in der Forschung sowie Implikationen für die Marketingpraxis abgeleitet.

Der **Beitrag 3** mit dem Titel „**Understanding users’ switching behavior toward sustainable search engines: An empirical study from the perspective of the push-pull-mooring model**“ befindet sich derzeit im Begutachtungsprozess des *Journal of Services Marketing* und untersucht – vor dem Hintergrund der zunehmenden Umweltbelastungen durch digitale Infrastruktur – die Determinanten der Wechselintention sowie des tatsächlichen Wechselverhaltens von Internetnutzern von herkömmlichen Suchmaschinen zu ökologisch nachhaltigen Suchmaschinen.

Basierend auf einer Online-Befragung mit zwei Messzeitpunkten ($N = 225$; 58,8 % männlich; $M_{\text{Alter}} = 41,84$; $SD_{\text{Alter}} = 11,72$) wird ein erweitertes PPM-Modell getestet, das neben den in den Beiträgen 1 und 2 identifizierten am häufigsten verwendeten Push-, Pull- und Mooring-Variablen drei kontextspezifische, nachhaltigkeitsbezogene Variablen integriert. Die Ergebnisse zeigen, dass der Pull-Faktor – bestehend aus Attraktivität der Alternative, subjektiver Norm, wahrgenommener Nützlichkeit und wahrgenommenen Umweltvorteilen – die Wechselintention stark erhöht, während der Mooring-Faktor – bestehend aus Wechselkosten, Trägheit und geringem Bewusstsein für nachhaltigen Konsum – die Wechselintention stark reduziert. Darüber hinaus hemmt der Mooring-Faktor nicht nur direkt die Wechselintention, sondern schwächt zugleich den Einfluss des Pull-Faktors auf die Wechselintention und die Beziehung zwischen Wechselintention und Wechselverhalten. Im Gegensatz dazu hat der Push-Faktor – bestehend aus wahrgenommener Umweltbedrohung und schlechter Servicequalität – keinen Effekt auf die Wechselintention. Die Wechselintention wirkt sich positiv auf das tatsächliche Wechselverhalten aus.

Mit diesem Beitrag wird das PPM-Modell im Kontext ökologisch nachhaltiger, digitaler Dienstleistungen angewendet. Darüber hinaus liefert der Beitrag seltene empirische Evidenz zu tatsächlichem Wechselverhalten und verdeutlicht, dass der Mooring-Faktor die Wechselintention nicht nur direkt reduziert, sondern auch den Einfluss von Wechselintention auf Wechselverhalten schwächt. Aufbauend auf diesen Ergebnissen werden Handlungsempfehlungen für Anbieter ökologisch nachhaltiger Suchmaschinen sowie für politische Entscheidungsträger abgeleitet, um Anreize für einen Wechsel zu schaffen und bestehende Barrieren gezielt abzubauen.

Der **Beitrag 4** mit dem Titel „**From conversational agents back to human agents? A two-wave study of the drivers and inhibitors of customer switching behavior**“ befindet sich derzeit im Begutachtungsprozess bei *Computers in Human Behavior* und untersucht – vor dem Hintergrund der anhaltenden Debatte über die Verdrängung menschlicher Arbeitskräfte durch KI-basierte Maschinen – die Determinanten der Wechselintention sowie des tatsächlichen Wechselverhaltens von Kunden von Chatbots zu menschlichen Kundenserviceitarbeitern.

Basierend auf einer Online-Befragung mit zwei Messzeitpunkten ($N = 240$; 62,5 % männlich; $M_{\text{Alter}} = 43,31$; $SD_{\text{Alter}} = 11,75$) wird ein erweitertes PPM-Modell getestet, das neben den in den Beiträgen 1 und 2 identifizierten meist genutzten Push-, Pull-, und Mooring-Variablen sechs kontextspezifische Variablen integriert. Die Ergebnisse zeigen, dass der Pull-Faktor, der in erster

Linie durch die wahrgenommene Nützlichkeit menschlicher Servicemitarbeiter geprägt ist, die Wechselintention erhöht. Der Mooring-Faktor, hauptsächlich getrieben von Trägheit, hemmt die Wechselintention hingegen. Überraschenderweise reduziert der Push-Faktor, der vor allem von Unzufriedenheit und wahrgenommener Ineffizienz des Chatbots geprägt ist, die Wechselintention, was in diesem Kontext darauf hindeutet, dass Kunden sich bei negativen Erfahrungen mit dem Chatbot eher vollständig vom Kundenservice abwenden, anstatt auf menschliche Unterstützung umzusteigen. Darüber hinaus erweist sich die wahrgenommene Schwierigkeit der Aufgabe als zentrale Antezedens, indem sie sowohl den Push- als auch den Pull-Faktor positiv beeinflusst, während sie den Mooring-Faktor negativ beeinflusst. Schließlich zeigt sich, dass die Wechselintention einen positiven Einfluss auf das tatsächliche Wechselverhalten hat.

Insgesamt verdeutlichen die Ergebnisse, dass der derzeitige Wettbewerbsvorteil menschlicher Kundenservicemitarbeiter in ihrer Fähigkeit liegt, komplexe Serviceanfragen zu bearbeiten. Chatbots stoßen bei schwierigen Aufgaben derzeit an ihre Grenzen, beispielsweise aufgrund eingeschränkten Verständnisses oder limitierten Zugangs zu Informationen, sodass menschliche Unterstützung unverzichtbar bleibt. Mit zunehmender technologischer Weiterentwicklung könnten Chatbots jedoch in der Lage sein, das gesamte Spektrum an Serviceanfragen zu bewältigen, wodurch dieser Vorteil schrittweise an Bedeutung verlieren dürfte. Aufbauend auf diesen Ergebnissen werden Handlungsempfehlungen für Theorie und Praxis abgeleitet.

Der **Beitrag 5** mit dem Titel „**If it ain't broke, don't fix it? Understanding how an inertia mindset mitigates the effect of service failure on customer defection**“ wurde im Jahr 2023 in den *Proceedings of the European Marketing Academy Conference* veröffentlicht und untersucht, inwieweit eine Trägheitsmentalität (engl. inertia mindset) die Abwanderungsintention (engl. defection intention) von Kunden im Falle von Servicefehlern (engl. service failure) verringern kann.

Basierend auf der Status-quo-Bias-Theorie (Samuelson & Zeckhauser, 1988) und der Customer-Inertia-Marketing-Theorie (Henderson et al., 2021) wird ein Forschungsmodell entwickelt, das untersucht, über welche Mechanismen eine Trägheitsmentalität entsteht und wie diese die Abwanderungsintention beeinflusst. Dabei werden insbesondere die Rollen von Minimierung des Denkens (engl. thinking minimization) und Minimierung des Bedauerns (engl. regret minimization) als zentrale psychologische Antezedenzen einer Trägheitsmentalität betrachtet.

Um die im Forschungsmodell aufgestellten Hypothesen zu testen, wurde eine Online-Befragung mit einem einfaktoriellen Between-Subjects-Design im Kontext von Video-Streamingdiensten durchgeführt (N = 442; 76,7 % männlich; $M_{\text{Alter}} = 39,26$; $SD_{\text{Alter}} = 11,45$). Die Ergebnisse der Strukturgleichungsmodellierung zeigen, dass eine Trägheitsmentalität sowohl die Abwanderungsintention direkt reduziert als auch den negativen Einfluss eines Servicefehlers auf die Abwanderungsintention abschwächt. Zudem wird bestätigt, dass Minimierung des Denkens und Minimierung des Bedauerns psychologische Antezedenzen einer Trägheitsmentalität sind, welche wiederum durch die Konsistenz des vorherigen Konsums (engl. prior consumption consistency) und das Ausmaß des vorherigen Konsums (engl. prior consumption magnitude) beeinflusst werden.

Die Ergebnisse erweitern das theoretische Verständnis dafür, wie stabile Kundenbeziehungen trotz negativer Erfahrungen aufrechterhalten werden können, und bieten Unternehmen konkrete Ansatzpunkte, um ihre Wiedergutmachungsmaßnahmen zu optimieren.

Der **Beitrag 6** mit dem Titel „**Enhancing virtual reality experiences in grocery retailing: The impact of audio priming on spatial presence and retailer outcomes**“ wurde im Jahr 2025 in *The International Review of Retail, Distribution and Consumer Research* veröffentlicht und untersucht, ob Audio-Priming die räumliche Präsenz (engl. spatial presence) in VR-Erlebnissen steigern kann. Das Ziel des Beitrags ist es, die Wirkung zweier Arten von Audio-Priming – auf eine Bauernhofatmosphäre bezogen versus auf VR-Technologie bezogen – auf die räumliche Präsenz in virtuellen Stallbesichtigungen zu prüfen und zu analysieren, wie diese Präsenz das wahrgenommene Vergnügen (engl. perceived enjoyment) sowie daraus resultierende kaufrelevante Zielgrößen beeinflusst.

Basierend auf theoretischen Grundlagen zu VR, räumlicher Präsenz, Priming und der Fluency-Theorie wird ein Forschungsmodell entwickelt, das den Einfluss von Audio-Priming auf die räumliche Präsenz, den Einfluss räumlicher Präsenz auf wahrgenommenes Vergnügen sowie den Einfluss des wahrgenommenen Vergnügens auf die Weiterempfehlungsintention und die Einstellung gegenüber dem Händler untersucht.

Zur Überprüfung der im Forschungsmodell aufgestellten Hypothesen wurde ein Labor-Experiment mit 57 Teilnehmern (57,9 % männlich; $M_{\text{Alter}} = 24,58$; $SD_{\text{Alter}} = 8,75$) durchgeführt, die zufällig einer Kontrollgruppe oder einer von zwei Priming-Gruppen zugeordnet wurden. Das VR-Erlebnis

bestand aus einer 360°-Video-Stallbesichtigung, präsentiert über ein VR-Headset. Die Ergebnisse der Strukturgleichungsmodellierung zeigen, dass VR-Technologie-Priming die räumliche Präsenz signifikant erhöht, während Bauernhofatmosphäre-Priming keinen Effekt hat. Eine erhöhte räumliche Präsenz steigert das wahrgenommene Vergnügen, welches wiederum sowohl die Weiterempfehlungsintention als auch die Einstellung gegenüber dem Händler positiv beeinflusst.

Die Studie liefert den erstmaligen empirischen Nachweis, dass Audio-Priming – bezogen auf die VR-Technologie – die räumliche Präsenz in VR-Erlebnissen steigern kann, und erklärt diesen Effekt mithilfe der Fluency-Theorie. Darüber hinaus werden konkrete Empfehlungen für den strategischen Einsatz von Audio-Priming in virtuellen Stallbesichtigungen im Lebensmitteleinzelhandel abgeleitet, um die Konsumentenakzeptanz solcher VR-Angebote zu erhöhen, die Transparenz in der landwirtschaftlichen Nutztierhaltung zu fördern, das Vertrauen in den Händler zu stärken und eine Differenzierung vom Wettbewerb zu ermöglichen.

Die ausgewählten Beiträge lassen sich anhand der **Art der Datenbasis** sowie der **Determinanten des Wechsels** systematisch einordnen (Abbildung 2).

Die Beiträge 1 und 2 basieren als Meta-Analysen auf **Sekundärdaten** aus bereits veröffentlichten Studien, die das PPM-Modell angewendet haben, und dienen der Strukturierung der bis dahin fragmentierten Forschung. Aufbauend darauf greifen die Beiträge 3 bis 6 auf **Primärdaten** zurück, die durch eigens für die jeweiligen Forschungsfragen konzipierte Erhebungen gewonnen und ausgewertet wurden.

Mit Blick auf die Determinanten des Wechsels ergeben sich folgende Unterschiede: Die Beiträge 1 und 2 befassen sich als Meta-Analysen mit dem PPM-Modell in seiner Gesamtheit und berücksichtigen damit **Push-, Pull- und Mooring-Variablen**. Daran anknüpfend wenden die Beiträge 3 und 4 das Modell ebenfalls in seiner Gesamtheit an, wobei sie die in den Beiträgen 1 und 2 gewonnenen Erkenntnisse systematisch zur Beantwortung ihrer jeweiligen Forschungsfragen nutzen.

Beitrag 5 hingegen fokussiert ausschließlich auf die **Mooring-Variable** Trägheit, die in den Beiträgen 1 und 2 als eine der am häufigsten untersuchten Mooring-Variablen identifiziert wurde und sich in den Beiträgen 3 und 4 jeweils als besonders erklärungsrelevant erwiesen hat. Dabei werden insbesondere psychologische Antezedenzen dieser Variable untersucht.

Während die Beiträge 1 und 2 zeigen, dass die in der PPM-Literatur am häufigsten untersuchten Variablen überwiegend kognitiver Natur sind, rückt Beitrag 6 mit dem wahrgenommenen Vergnügen bewusst eine affektive Variable in den Mittelpunkt, deren Integration das Erklärungspotenzial des PPM-Modells erweitern kann (Marx, 2025). Konzeptionell lässt sich wahrgenommenes Vergnügen als **Pull-Variable** einordnen, da es einen positiven Einfluss am Zielort – der virtuellen Stallbesichtigung – widerspiegelt. Der VR-Kontext eignet sich besonders für die Untersuchung affektiver Variablen, da virtuelle Realitäten durch die Simulation kontrollierter, immersiver Umgebungen intensive Emotionen hervorrufen können (Somarathna et al., 2023). Anders als in klassischen PPM-Studien wurde in Beitrag 6 die Wechselintention nicht direkt erhoben, da für die Konsumenten in diesem Kontext keine klare Entscheidungssituation zwischen zwei Alternativen bestand. Stattdessen lag der Fokus auf der Akzeptanz der virtuellen Stallbesichtigung als neuem Angebot. Die Akzeptanz eines neuen informationstechnologischen Angebots – wie der virtuellen Stallbesichtigung – wird in der Informationstechnologie-Akzeptanzforschung üblicherweise über die Nutzungsintention oder die tatsächliche Nutzung erfasst (Venkatesh et al., 2003). Da die Nutzung der virtuellen Stallbesichtigung im Rahmen des Labor-Experiments jedoch vorgegeben wurde, wäre die Ex-post-Erhebung der Nutzungsintention oder tatsächlichen Nutzung nach der Durchführung nicht sinnvoll gewesen. Stattdessen musste eine Variable erfasst werden, die der initialen Akzeptanz nachgelagert ist. Die Erhebung der Wiedernutzungsintention als gängigem Indikator fortwährender Akzeptanz (Bhattacharjee, 2001) wäre im vorliegenden Studiendesign ebenfalls nicht sinnvoll gewesen, da hierfür die Bedingungen einer zukünftigen Nutzungssituation klar hätten skizziert werden müssen, wodurch die Messung stark kontextabhängig gewesen wäre. Vor diesem Hintergrund wurde die Weiterempfehlungsintention als eine kontextunabhängige, der initialen Akzeptanz nachgelagerte Variable gewählt (Chotiyaputta & Shin, 2022; Venkatesh et al., 2016). Die Weiterempfehlungsintention lässt wiederum Rückschlüsse auf potenzielle Wechselentscheidungen zu (von Wangenheim & Bayón, 2004) – im Kontext dieser Studie etwa darauf, ob Konsumenten in entsprechenden Entscheidungssituationen die virtuelle Stallbesichtigung als Alternative zur Präsenz-Stallbesichtigung in Betracht ziehen würden.

		Determinanten des Wechsels		
		Push	Pull	Mooring
Art der Datenbasis	Primärdaten	B3 B4	B3 B4 B6	B3 B4 B5
	Sekundärdaten	B1 B2	B1 B2	B1 B2

Abbildung 2: Systematische Einordnung der ausgewählten Beiträge

Quelle: Eigene Darstellung

In Tabelle 3 wird abschließend eine Übersicht der ausgewählten Beiträge gegeben, bevor diese in Kapitel 4 in voller Länge präsentiert werden.

Beitrag	Autoren (Jahr)	Titel	Methodik	Theorie/Modell	Outlet (Ranking) ¹⁶	Status
1	Marx, T., Harms, R., & Fröbel, L. (2023)	The push-pull-mooring model of service switching: A meta-analysis	Systematische Literaturübersicht, Meta-Analyse, OSMASEM	PPM-Modell	Advances in Consumer Research (C)	Veröffentlicht (als Short Abstract)
2	Marx, T. (2025)	The push-pull-mooring model of consumer service switching: A meta-analytical review to guide future research	Systematische Literaturübersicht, Meta-Analyse, OSMASEM, Moderationsanalyse	PPM-Modell	Journal of Service Theory and Practice (C)	Veröffentlicht
3	Marx, T. (2025)	Drivers and barriers of switching to sustainable services: Empirical evidence from a two-wave study of sustainable search engines	Online-Befragung (Längsschnitt, zwei Messungen), PLS-SEM, Moderationsanalyse	PPM-Modell	Journal of Services Marketing (C)	In Begutachtung (Revise & Resubmit, zur Wiedereinreichung in Vorbereitung)
4	Marx, T., & Hubert, M. (2025)	From conversational agents back to human agents? A two-wave study of the drivers and inhibitors of customer switching behavior	Online-Befragung (Längsschnitt, zwei Messungen), PLS-SEM, Logistische Regression	PPM-Modell	Computers in Human Behavior (B)	In Begutachtung
5	Marx, T. (2023)	If it ain't broke, don't fix it? Understanding how an inertia mindset mitigates the effect of service failure on customer defection	Online-Befragung (Querschnitt), Online-Experiment mit einfaktoriellem Between-Subjects-Design, CB-SEM, Moderationsanalyse	Status-quo-Bias-Theorie, Customer-Inertia-Marketing-Theorie	Proceedings of the European Marketing Academy Conference (D)	Veröffentlicht
6	Marx, T., Welle, G., & Gier-Reinartz, N. R. (2025)	Enhancing virtual reality experiences in grocery retailing: The impact of audio priming on spatial presence and retailer outcomes	Laborexperiment mit einfaktoriellem Between-Subjects-Design und Ex-ante- sowie Ex-post-Befragung, PLS-SEM	Priming, Fluency-Theorie, Spatial-Presence-Theorie	The International Review of Retail, Distribution and Consumer Research (C)	Veröffentlicht

Tabelle 3: Übersicht der ausgewählten Beiträge

Quelle: Eigene Darstellung

¹⁶ Das Ranking des jeweiligen Outlets basiert auf der Bewertung des Verbands der Hochschullehrerinnen und Hochschullehrer für Betriebswirtschaft e. V. (VHB) zum Zeitpunkt der Einreichung bzw. Veröffentlichung. Das VHB-Rating 2024 ersetzt das bislang gültige VHB-JOURQUAL 3 aus dem Jahr 2015.

4 Ausgewählte Beiträge¹⁷

4.1 Beitrag 1: The push-pull-mooring model of service switching: A meta-analysis¹⁸

Autoren	Tobias Marx, Regina Harms, Lara Fröbel
Zitation	Marx, T., Harms, R., & Fröbel, L. (2023). The push-pull-mooring model of service switching: A meta-analysis. <i>Advances in Consumer Research</i> , 51, 970.
URL	https://acr.memberclicks.net/assets/Proceedings/Volume%2051%20-%20complete%20book.pdf
Keywords	-
Status	Veröffentlicht

Tabelle 4: Kurzübersicht zu Beitrag 1

Quelle: Eigene Darstellung

4.1.1 Short Abstract

For years, the push-pull-mooring (PPM) model has been used frequently by scholars to explain consumers' service switching intentions and behaviors. However, empirical evidence about the PPM model remains fragmented and ambiguous. This study provides the first comprehensive overview and meta-analytical test of the PPM model to help guide future research systematically.

4.1.2 Extended Abstract

For years, the push-pull-mooring (PPM) model—as introduced to service research by Bansal, Taylor, and James (2005)—has been used by scholars to explain consumers' service switching intentions and behaviors. Adapted from migration research (Bogue 1969; Lee 1966; Moon 1995), the PPM model suggests there are negative factors at the origin that push people away (push), and positive factors at the destination that pull people towards it (pull). Furthermore, personal and social

¹⁷ Die nachfolgenden Beiträge werden im Wortlaut sowie im Zitationsstil der jeweiligen Originalfassungen wiedergegeben. Gestaltungen im Fließtext, wie etwa Fett- oder Kursivsetzungen, entsprechen den Hervorhebungen der Originaltexte. Abweichend hiervon folgen die Nummerierungen von Abbildungen und Tabellen der fortlaufenden Zählung dieser Arbeit und nicht jener der einzelnen Beiträge. Aus gestalterischen Gründen können Abbildungen und Tabellen in den Beiträgen an anderer Stelle als in den Originalfassungen platziert sein.

¹⁸ Ein Vorläufer des Beitrags wurde zuvor bei der 8. Rostocker Dienstleistungstagung im Jahr 2023 eingereicht und im Rahmen eines Vortrags vorgestellt.

factors can inhibit or facilitate migration decisions (mooring). The analogy is straightforward: Consumers (migrants) switch (move) from one service (place) to another.

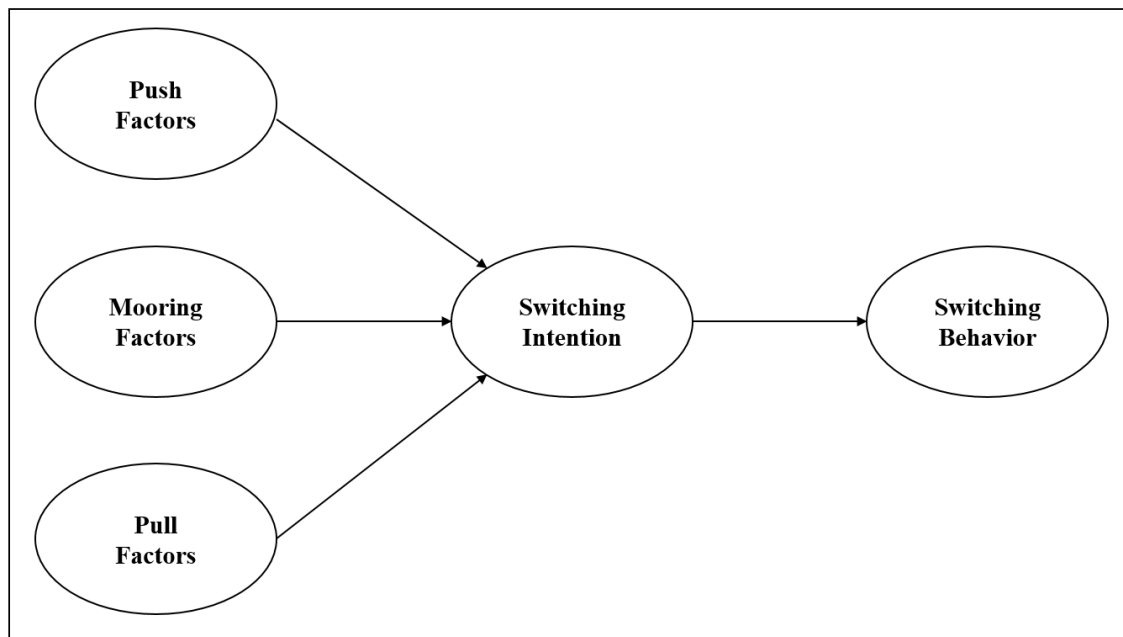


Abbildung 3: The PPM model of service switching by Bansal et al. (2005)

The PPM model provides a useful theoretical framework to include different predictor variables commonly associated with service switching (e.g., dissatisfaction, switching costs) by categorizing them as push, pull, or mooring factors (Bansal et al. 2005). However, empirical evidence about the PPM model remains fragmented and ambiguous. The categorization of predictor variables, reported effect sizes, and effect directions vary considerably. In response, this meta-analysis seeks to provide a comprehensive overview of PPM model usage in the literature and to synthesize previously inconclusive findings.

We conducted an elaborate literature search to identify studies using the PPM model by searching the following electronic databases: Ebsco, Econbiz, Google Scholar, Jstor, Proquest, Scopus, SSRN, and Web of Science. Furthermore, we reviewed the references in all appropriate studies to find additional studies yet to be included in our database. The search yielded a total of 220 studies. Of these, 131 empirical-quantitative studies were included for further analysis. Based on these, we created a dataset containing all predictor variables used and their categorization as push, pull, or mooring factors. Figure 2 [hier: Abbildung 4] shows the most frequently used variables and their respective categorization.

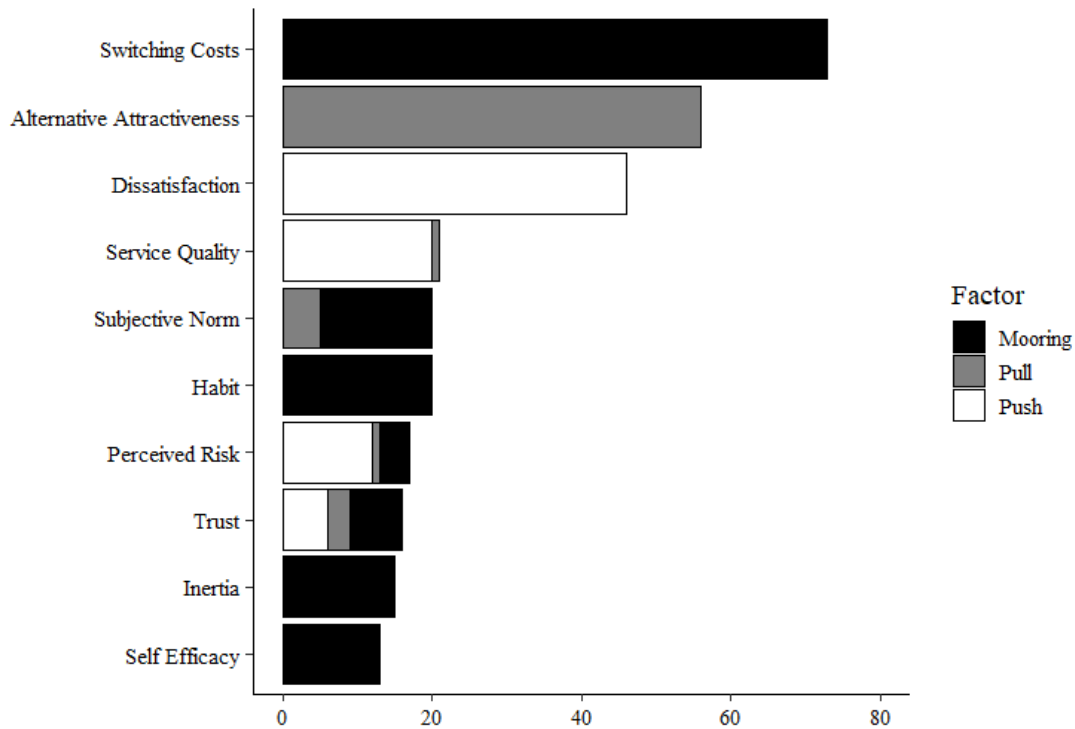


Abbildung 4: Most frequently used PPM variables

As figure 2 [hier: Abbildung 4] illustrates, categorization is ambiguous for some variables in the literature. In contrast, categorization for the three most frequently used variables (switching costs, alternative attractiveness, dissatisfaction) is unequivocal. Thus, we focus on these variables to develop our research model (figure 3 [hier: Abbildung 5]).

Dissatisfaction refers to *a psychological state that arises when consumers' experiences are coupled with disconfirmed expectations* (Oliver 1981). According to expectation-confirmation theory, consumers' intention to discontinue service use is primarily determined by their dissatisfaction (Anderson and Sullivan 1993; Oliver 1980). We thus hypothesize that dissatisfaction increases switching intention (H_1).

Switching costs can be defined as *consumers' perceived economic and psychological costs associated with changing from one alternative to another* (Jones, Mothersbaugh, and Beatty 2002). These costs are seldom explicitly assessed but become salient when consumers face reasons to consider switching (Burnham, Frels, and Mahajan 2003). As such, switching costs can be regarded as barriers that hold consumers in service relationships (Jones et al. 2000, 2002). Thus, we hypothesize that switching costs decrease switching intention (H_2).

Alternative attractiveness refers to *consumers' perceptions regarding the extent to which viable competing alternatives are available* (Jones et al. 2000). When consumers have few attractive alternatives, the likelihood of terminating an existing service relationship decreases as the perceived benefit of switching decreases (Jones et al. 2000). We thus assume that alternative attractiveness increases switching intention (H_3).

Switching intention can be defined as *consumers' intention to switch services*, whereas switching behavior refers to *consumers' actual switching behavior* (Ajzen 1991; Bansal et al. 2005). Intentions are generally considered the best predictor of behavior (Ajzen 1991). We thus hypothesize that switching intention increases switching behavior (H_4).

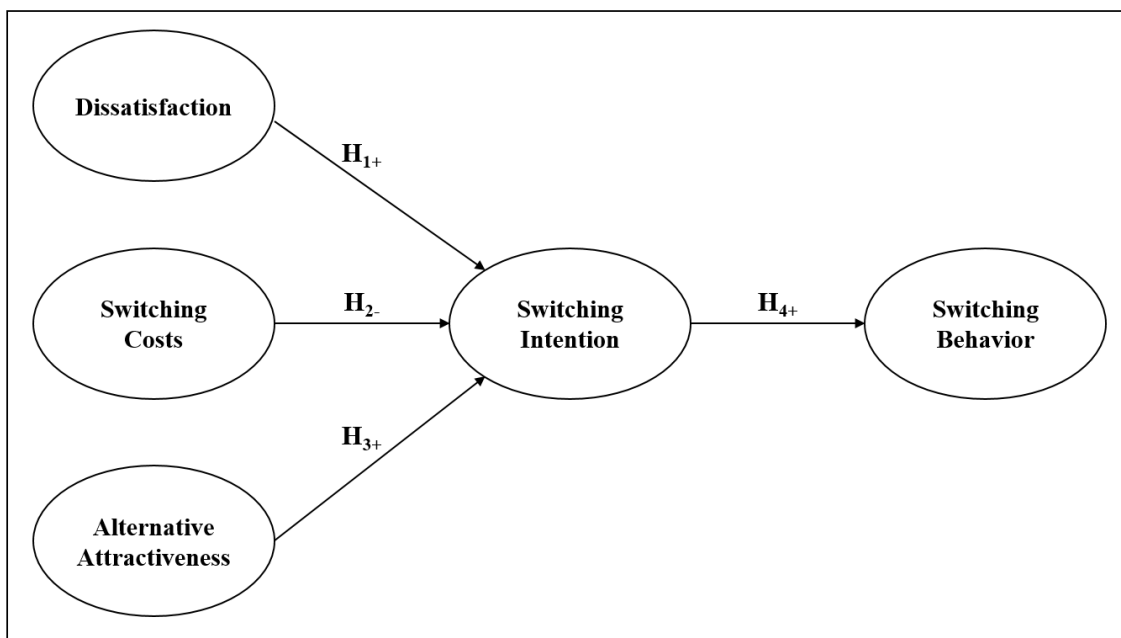


Abbildung 5: Research model

We used meta-analytic structural equation modeling (MASEM) to test our research model. MASEM refers to fitting structural equation models to meta-analytic data using correlation matrices (Jak and Cheung 2021). Our MASEM database includes (1) all empirical-quantitative PPM model studies that (2) report correlation matrices or metrics that we could transform into correlations (e.g., standardized betas; Peterson and Brown 2005), and (3) contain at least two variables from our research model. This final database includes 88 studies.

Out of the various MASEM methods available, one-stage MASEM is the most versatile method, as it can evaluate effects of continuous and categorical moderators without creating subgroups (Jak and Cheung 2021). Furthermore, it has been shown to work well with incomplete data (Jak and Cheung 2020) and is thus well suited for our analysis.

Parameters	<i>k</i>	<i>N</i>	Estimate	Standard Error	<i>z</i> value	<i>p</i> value
<i>Hypothesized paths:</i>						
DS → SI	41	15,463	.219	.041	5.391	<.001
SC → SI	60	20,823	-.167	.044	-3.769	<.001
AA → SI	44	17,456	.380	.035	10.973	<.001
SI → SB	10	4,530	.607	.049	12.495	<.001
<i>Correlations:</i>						
DS ↔ AA	16	6,805	.244	.055	4.419	<.001
DS ↔ SC	20	7,272	-.026	.066	-.396	.692
AA ↔ SC	20	6,051	-.093	.065	-1.413	.158

Tabelle 5: One-stage MASEM results

Note. $R^2_{SI}=73\%$, $R^2_{SB}=63\%$, *k*: Number of correlations per relation, *N*: Total number of respondents across *k* samples, DS: Dissatisfaction, SC: Switching Costs, AA: Alternative Attractiveness, SI: Switching Intention, SB: Switching Behavior

Table 1 [hier: Tabelle 5] summarizes the MASEM results for our research model. Based on fit indices ($\chi^2/d.f.=1.507$, $RMSEA=.004$, $SRMR=.082$, $TLI=.975$, $CFI=.993$), the overall model fit can be considered adequate. The results show that dissatisfaction ($\beta=.219$, $p<.001$, H₁) and alternative attractiveness ($\beta=.380$, $p<.001$, H₃) increase switching intention, which has a positive effect on switching behavior ($\beta=.607$, $p<.001$, H₄). Moreover, the results show that switching costs decrease switching intention ($\beta=-.167$, $p<.001$, H₂). Thus, all hypotheses can be confirmed.

This study provides the first comprehensive overview and meta-analytical test of the PPM model. The results are valuable to researchers in the field and can help guide future research systematically. However, there are critical challenges that still need to be addressed. First, we intend to ask the authors of the studies in our database for missing information. Second, we plan to contact scholars in the field to ask for unpublished and currently inaccessible work. Finally, just like migration decisions (e.g., moving within or between countries), service switching decisions are nuanced. We thus aim to address these nuances through moderation analysis using service-based moderators (e.g., intangibility, coproduction) and demographic moderators (e.g., age, gender) in future research.

4.2 Beitrag 2: The push-pull-mooring model of consumer service switching: A meta-analytical review to guide future research

Autoren	Tobias Marx
Zitation	Marx, T. (2025). The push-pull-mooring model of consumer service switching: A meta-analytical review to guide future research. <i>Journal of Service Theory and Practice</i> , 35(7), 1–29.
URL	https://doi.org/10.1108/JSTP-06-2024-0201
Keywords	Push-pull-mooring model, Meta-analysis, Meta-analytical review, Meta-analytic structural equation modeling, Service switching, Switching behavior, Switching intention, Dissatisfaction, Alternative attractiveness, Switching costs
Status	Veröffentlicht

Tabelle 6: Kurzübersicht zu Beitrag 2

Quelle: Eigene Darstellung

4.2.1 Abstract

Purpose: For nearly two decades, the push-pull-mooring (PPM) model has been used frequently by scholars to explain consumers' service switching intention and behavior. However, heterogeneity and incomparability between PPM model studies are prevalent issues: The chosen predictor variables, their categorization, their measurement, reported effect sizes, and effect directions vary considerably. By addressing these issues, the present meta-analytical review enables future researchers applying the PPM model to identify relevant variables and use valid measurements.

Design/methodology/approach: Based on 148 empirical studies employing the PPM model, the variables used to predict consumers' service switching intention and behavior, their frequency of use, their categorization into push, pull, and mooring factors, and their measurement are assessed. The effect sizes and directions of the relationships between these variables and consumers' service switching intention and behavior are analyzed using meta-analytic structural equation modeling. Additionally, the predictive capacity of this model and the influence of moderators are assessed.

Findings: Among the 148 empirical studies, 382 different independent variables were used. The three most frequently used and distinctly categorized independent variables are dissatisfaction (push), alternative attractiveness (pull), and switching costs (mooring). Overall, 152 unique sources

were cited to measure these variables and the dependent variables. Dissatisfaction and alternative attractiveness increase switching intention, which positively affects switching behavior, while switching costs decrease switching intention. The model explains 30% of the variance in switching intention and 31% of the variance in switching behavior.

Originality: This study provides the first meta-analytical review of the PPM model to guide future research systematically.

4.2.2 Introduction

For nearly two decades, the push-pull-mooring (PPM) model—as introduced to service research by Bansal et al. (2005)—has been used by scholars to explain consumers' service switching intention and behavior. Adapted from migration research (Bogue, 1969; Lee, 1966; Moon, 1995; Ravenstein, 1885), the PPM model posits that negative factors at the origin push individuals away (push) and positive factors at the destination pull them towards it (pull). Furthermore, personal and social factors can inhibit or facilitate migration decisions (mooring). When applying the PPM model to service research, the analogy is straightforward: Consumers (migrants) switch (move) from one service provider (place) to another. The PPM model provides a sound theoretical framework to include different predictor variables commonly associated with service switching intention and behavior by categorizing them as push, pull, or mooring factors (Bansal et al., 2005). Extensive studies on the PPM model in service research have resulted in a substantial body of knowledge. However, heterogeneity and incomparability between PPM model studies are prevalent issues: The chosen predictor variables, their categorization, their measurement, reported effect sizes, and effect directions vary considerably. This is problematic for a number of reasons: The lack of comparability across studies undermines the ability to draw conclusions about the efficacy of the PPM model. Additionally, conflicting results regarding effect sizes and directions make it difficult to identify clear patterns. Furthermore, inconsistent conceptualization and measurement hinder the theoretical development of the PPM model. Collectively, these issues diminish the utility of the PPM model for researchers and practitioners alike. To resolve this, this study provides the first comprehensive overview and meta-analytical test of the PPM model.

The contributions to the literature are numerous: First, the different variables used to predict consumers' service switching intention and behavior in PPM model studies are assessed. Based on this, an analysis is conducted on how these variables are categorized into push, pull, and mooring

factors and which ones are used most frequently. Second, differences in the measurement of these variables across the underlying studies are investigated. Third, the effect sizes and directions of the relationships between the most frequently used push, pull, and mooring variables (i.e., dissatisfaction, switching costs, alternative attractiveness) and consumers' service switching intention and behavior are assessed. Thereby, this meta-analytical review provides a benchmark, allowing researchers to identify anomalous results and to design studies with appropriate sample sizes. Moreover, this allows for empirical generalizations about which aspects practitioners should focus on in their acquisition and retention strategies. Fourth, the average predictive capacity of the PPM model using these variables is assessed. Finally, the influence of moderators on the effects of dissatisfaction, switching costs, and alternative attractiveness on consumers' switching intention is examined. This allows for conclusions on which variables are particularly relevant under specific conditions. Thus, the following research questions are answered:

- (1) Which variables are used to predict consumers' service switching intention and behavior in PPM model studies?*
- (2) How are these variables categorized into push, pull, and mooring factors?*
- (3) Which of these variables are most frequently used?*
- (4) Which measurement scales are most frequently used to operationalize these variables?*
- (5) What are the effect sizes and directions of the relationships between the most frequently used push, pull, and mooring variables and consumers' service switching intention and behavior?*
- (6) What is the predictive capacity of the PPM model using these variables in explaining the variance in consumers' service switching intention and behavior?*
- (7) What moderators affect the relationships between the most frequently used push, pull, and mooring variables and consumers' service switching intention?*

By addressing these questions, this paper offers guidance for future researchers applying the PPM model to improve their studies. The key issues in PPM model studies and how this meta-analytical review addresses them are summarized in Table 1 [hier: Tabelle 7]. To achieve this, the rest of this paper is organized as follows: Chapter 2 briefly reviews the PPM model. Chapter 3 outlines the methodological approach. Chapter 4 presents the conceptual framework and hypotheses. Chapter 5 reveals the meta-analytical findings. Chapter 6 discusses the findings, highlighting their

theoretical and practical significance. Lastly, Chapter 7 outlines the limitations of this study and proposes directions for future research.

Issue	Status quo	Future research based on meta-analytical insights
Predictor variable choice	Predictor variables are selected arbitrarily across PPM model studies without a clear rationale.	This meta-analytical review identifies the ten most frequently used predictor variables in PPM model studies, providing a reference point. This enables researchers to justify their variable selection based on cumulative evidence.
Predictor variable categorization	Predictor variables are categorized inconsistently across PPM model studies.	The meta-analytical review identifies the categorization for the ten most frequently used predictor variables in PPM model studies, providing a reference point. This allows researchers to justify their variable categorization based on cumulative evidence.
Measurement	Predictor variables and dependent variables are measured inconsistently across PPM model studies.	This meta-analytical review provides an overview of the most frequently used valid measurement scales, encouraging standardization. This enables researchers to select measurement scales that improve comparability across studies.
Effect sizes	Effect sizes differ across PPM model studies with no benchmark for comparison.	The meta-analytical review provides a benchmark for effect sizes. This allows researchers to identify anomalous results and ensure appropriate sample sizes in their study designs.
Effect directions	Effect directions differ across PPM model studies with no benchmark for comparison.	This meta-analytical review provides a benchmark for effect directions. This enables researchers to identify anomalous results.
Variance explained	Variance explained differs across PPM model studies with no benchmark for comparison.	This meta-analytical review provides a benchmark for variance explained. This enables researchers to identify anomalous results.
Moderators	Individual level moderators are investigated.	This meta-analytical review provides insights into study level moderators. This provides researchers with a further explanation for differences in effect sizes.

Tabelle 7: Issues in PPM model studies and meta-analytical insights to improve future research

4.2.3 Push-Pull-Mooring Model

The PPM model, initially developed in migration research (Bogue, 1969; Lee, 1966; Moon, 1995; Ravenstein, 1885), explains why individuals leave their place of origin to move to a new destination. The model has three components: push, pull, and mooring factors. Push factors are negative factors at the origin that motivate individuals to leave (Stimson & Minnery, 1998). Pull factors are positive factors at the destination that attract individuals to migrate there (Moon, 1995). Migration research on push factors (e.g., economic recession, natural catastrophe) and pull factors (e.g., favorable climate, superior infrastructure) has a long history, dating back as early as the nineteenth century (Ravenstein, 1885). Throughout this extensive period, researchers have primarily focused on these factors as they induce migration, with comparatively less attention given to their counterparts—positive factors at the origin and negative factors at the destination (Bansal et al., 2005; Lee, 1966). Starting with key articles by Wolpert (1965, 1966), there was a shift in focus toward understanding how migrants perceive push and pull factors, realizing that it is not the actual factors themselves but the perceptions of these factors that result in migration (Lee, 1966). This led researchers to consider personal (e.g., personal anxiety) and social factors (e.g., family attachments) in influencing migration decisions (Bansal et al., 2005). Lee (1966) introduced the concept of “intervening obstacles,” which Jackson (1986) refined to “intervening variables,” acknowledging that these factors can either facilitate or inhibit migration. This idea was further developed into the concept of mooring factors, which are personal and social factors that can hold potential migrants to their place of origin or facilitate migration to the new destination (Longino, 1992; Moon, 1995). In migration research, a key distinction among these factors is the level of control individuals have over them. Push factors and pull factors are conceptualized as being outside the individual’s control (Bogue, 1969; Moon, 1995), whereas mooring factors are conceptualized as being, to some extent, within the individual’s control (Moon, 1995). Another important distinction is that individuals generally weigh push and pull factors against each other in a direct comparison, while mooring factors are assessed separately, providing the context for this comparison (Lee, 1966). Furthermore, mooring factors can moderate the relationships between push and pull factors and the migration decision (Lee, 1966).

Bansal et al. (2005) first applied the PPM model in service research to explain consumers’ switching intention and behavior between auto repair and hair styling services. In doing so, they used low quality, low satisfaction, low value, low trust, low commitment, and high price

perceptions to conceptualize the push factor; alternative attractiveness to conceptualize the pull factor; and unfavorable attitude towards switching, unfavorable subjective norms, high switching costs, infrequent prior switching behavior, and low variety seeking to conceptualize the mooring factor. They found that the PPM model was highly effective in predicting the dependent variables and called for further research in this field. Since then, the PPM model has been widely used in various contexts to explain switching intention and behavior, reflecting its growing popularity in service research. For example, Zengyan et al. (2009) applied the model to social networking services, Ye and Potter (2011) used it to study web browsers, and Wu et al. (2017) applied it to examine cloud storage services. However, all of these studies differ in their selection of variables to conceptualize the push, pull, and mooring factors, as well as in their measurement of these variables.

In more detail, when applying the PPM model, Bansal et al. (2005) model the push, pull, and mooring factors as higher-order constructs. Specifically, they model them as reflective-reflective second-order constructs (Sarstedt et al., 2019) consisting of lower-order subdimensions such as subjective norms, switching costs, and alternative attractiveness. Bansal et al. (2005) demonstrate that the model with higher-order constructs explains more variance in switching intention (68%) than the model with direct effects, in which the lower-order subdimensions directly influence switching intention (61%). Nevertheless, most studies using the PPM model use the model with direct effects. Of the 148 studies identified as eligible in the third step of the data collection process in Chapter 3, 101 use the direct effects approach, while only 47 use the model with higher-order constructs.

As a result, a meta-analysis of the higher-order constructs is not feasible, not least because the higher-order constructs in each study are composed of different lower-order constructs. In this respect, the typical criticism of inappropriate comparisons in meta-analyses would apply (Cortina, 2003). Thus, this meta-analysis of the PPM model will focus on the lower-order constructs. The methodology is first reported in Chapter 3, based on which the specific variables for the conceptual model were selected. The conceptual model is then presented in Chapter 4.

4.2.4 Methodology

4.2.4.1 Selection and coding of studies

4.2.4.1.1 Data collection

In accordance with established guidelines for systematic literature reviews and meta-analyses (Liberati et al., 2009), this study's data collection process is illustrated in Figure 1 [hier: Abbildung 6]. Various search strategies were employed to build a comprehensive database (Eisend, 2017), including both published and unpublished studies from January 2005 to September 2023. First, a broad keyword search (search term: "push pull mooring") was conducted to identify studies using the PPM model by searching the following electronic databases: Ebsco, Econbiz, Google Scholar, Jstor, Proquest, Scopus, Social Science Research Network, and Web of Science. Additionally, the references in all appropriate studies were reviewed to find additional studies not yet included in the database. The search yielded a total of 270 unique studies. To address the file drawer problem (Rosenthal, 1979), the authors of the 148 PPM model studies identified as eligible in the data collection process were contacted via e-mail to inquire about any unpublished work. However, no additional studies could be obtained through this approach.

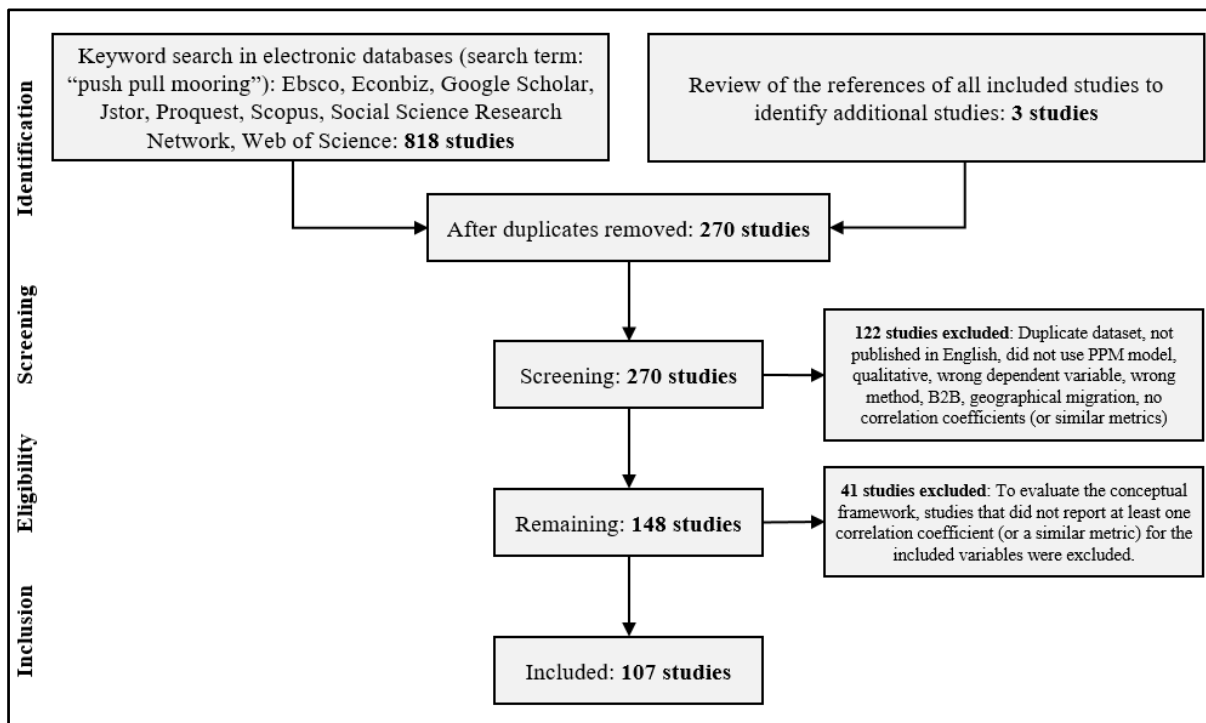


Abbildung 6: Data collection process

4.2.4.1.2 Exclusion criteria

Consistent with other meta-analyses (e.g., Eisend, 2006; Feng et al., 2021; Lütjens et al., 2022), studies using the same dataset as already included studies were excluded. Due to translation barriers, studies that were not published in English were excluded. Studies that appeared in the keyword search but, upon further inspection, did not use the PPM model (e.g., Bölen, 2020) were also excluded. Furthermore, all qualitative studies (e.g., Liu et al., 2021) were excluded. Studies with dependent variables that were inconsistent with the PPM model (i.e., not switching intention or behavior or synonymous variables) (e.g., Fu, 2011) and studies using methods (e.g., machine learning) unsuitable for this meta-analysis (e.g., Al-Mashraie et al., 2020) were also excluded. Moreover, studies on geographical migration (e.g., Kaur & Kaur, 2023) and studies from a B2B context (e.g., Suh & Kim, 2018) were excluded. The correlation coefficient was used to measure effect size, which is typical in meta-analyses in service research (e.g., Black et al., 2014; Blut et al., 2016; Feng et al., 2021; Ranjan et al., 2015). Consequently, studies that did not report correlation coefficients or where the correlation coefficient could not be derived from other reported statistics were excluded.

Based on the remaining 148 studies, a dataset containing all predictor variables used and their categorization as push, pull, or mooring factors was created. Figure 2 [hier: Abbildung 8] shows the ten most frequently used independent variables and their respective categorization. As Figure 2 [hier: Abbildung 8] illustrates, categorization is ambiguous for some variables in the literature. In contrast, categorization for the three most frequently used variables (i.e., switching costs, alternative attractiveness, dissatisfaction) is unequivocal. Thus, these variables were included in the conceptual framework (Figure 3 [hier: Abbildung 7]). The methodological reasons for not including additional predictor variables in the conceptual framework are explained in detail in Chapter 3.2.

4.2.4.1.3 Coding

In line with previous meta-analyses (e.g., Palmatier et al., 2006; Lütjens et al., 2022), many variables with definitions and operationalizations related to the determinants in the conceptual framework were found, albeit using different names. Following common practice in meta-analyses (e.g., Eisend, 2017), these variables were coded under the corresponding label of the focal

determinants (e.g., synonyms for switching intention include migration intention and shifting intention).

An extensive coding template, which included all required definitions and coding instructions, was created for the coding process. Using this template, the author and a trained research assistant carried out the coding. The initial intercoder reliability was .94. All inconsistencies were resolved through discussion.

4.2.4.1.4 Final dataset

The final dataset to evaluate the conceptual framework includes (1) all empirical-quantitative PPM model studies that (2) report correlation coefficients or metrics that could be transformed into correlation coefficients (e.g., beta coefficients; Peterson & Brown, 2005), and (3) contain at least two variables from the conceptual framework. Ultimately, 264 effect sizes were obtained from 109 independent samples, reported in 107 published or unpublished studies conducted between January 2005 and September 2023. A list of all studies included in this meta-analysis can be found in the supplementary material.

4.2.4.2 Meta-analytic structural equation modeling

Meta-analytic structural equation modeling (MASEM) was used to test the conceptual framework. MASEM refers to fitting structural equation models to meta-analytic data using correlation matrices (Jak et al., 2021). MASEM offers substantial advantages over meta-analyzing each effect in a model separately (Jak, 2015). First, it allows for the simultaneous evaluation of multiple predictors while accounting for dependencies between them (Jak & Cheung, 2020). Second, it provides an overall evaluation of model fit, which cannot be achieved through separate analyses of individual effects (Valentine et al., 2022). Modern multivariate MASEM methods use correlation matrices and sample sizes from each primary study as input (Jak & Cheung, 2020). In contrast, univariate MASEM methods pool correlation coefficients separately based on bivariate data and do not account for the dependency between correlations within studies (Jak, 2015). Because of these limitations, univariate MASEM methods are not recommended (Becker, 2000; Cheung & Chan, 2005; Jak, 2015).

The decision not to include additional variables in our conceptual framework stems from the fact that conducting multivariate MASEM with more than the three chosen independent variables is not possible with the data currently available. Including another variable would increase the number

of non-redundant, off-diagonal correlations from ten to 15 in each correlation matrix. Since the other predictor variables are used considerably less frequently (e.g., habit is included in only 27 of the 148 studies, Figure 2 [hier: Abbildung 8]), the resulting correlation matrices would be too sparse for the MASEM model to converge.

Further analysis was conducted using the metaSEM package in R (Cheung, 2015). When using MASEM, the five main considerations are (1) whether to use a fixed-effects or random-effects approach, (2) how to deal with possible study dependence, (3) how to deal with possible publication bias, (4) whether to correct estimates for attenuation and (5) how to incorporate judgments of study quality (Valentine et al., 2022).

4.2.4.2.1 Fixed-effects vs. random-effects

The fixed-effects approach assumes that all studies have the same population effect sizes, meaning any differences between observed effect sizes are solely attributed to sampling error (Hedges & Vevea, 1998). In contrast, the random-effects approach assumes that population effect sizes vary from study to study (Jak & Cheung, 2020), meaning differences between observed effect sizes may arise for reasons other than sampling error (Jak, 2015). For example, observed effect sizes might differ between studies due to variations in participants' age, education, or income (Borenstein et al., 2021; Valentine et al., 2022). The primary aim of the random-effects approach is to generalize the results of a meta-analysis beyond the included studies (Jak & Cheung, 2020). Since it is very likely that the population effect sizes differ between studies, the random-effects approach is generally preferred (Borenstein et al., 2021; Hedges, 2016). Therefore, the random-effects approach was used in this meta-analysis. Specifically, the one-stage MASEM (OSMASEM) approach, a multivariate random-effects MASEM method that does not involve two strictly separated stages, was used (Jak & Cheung, 2020). Among the various MASEM methods available, OSMASEM is the most versatile, as it can evaluate the effects of continuous and categorical moderators without creating subgroups (Jak & Cheung, 2022). Furthermore, it has been shown to perform well with incomplete data (Jak & Cheung, 2020), making it well-suited for this analysis.

4.2.4.2.2 Dependent estimates

In meta-analytic correlation matrices, the estimates are assumed to be independent (Valentine et al., 2022). Dependent estimates occur when one estimate offers insights about the magnitude or direction of another estimate (Van den Noortgate et al., 2013). Dependence may arise within

studies when multiple operationalizations of the same variables are used, resulting in multiple estimates for a specific correlation (Van den Noortgate et al., 2013). Since none of the studies included in this meta-analysis provided more than one operationalization for the same variable, it was unnecessary to account for dependence by averaging the dependent effect sizes (Valentine et al., 2022).

4.2.4.2.3 Publication bias

Publication bias occurs when a study remains unpublished due to a lack of statistically significant findings on its main outcomes (Valentine et al., 2022). Publication bias severely threatens the validity of conclusions derived from systematic reviews or meta-analyses. In the context of MASEM, publication bias results in overestimated relationships between variables and underestimated heterogeneity estimates (Valentine et al., 2022). Preventing publication bias is best achieved through an exhaustive literature search for relevant studies (Jak & Cheung, 2020; Vevea et al., 2019). This is crucial for all systematic reviews and meta-analyses but holds even greater significance in MASEM due to the lack of consensus on addressing potential publication bias in MASEM (Valentine et al., 2022). A comprehensive literature search was conducted in this meta-analysis, and authors were contacted to inquire about unpublished work. Furthermore, the presence of publication bias in this meta-analysis is unlikely because the PPM model typically encompasses various independent variables to predict switching intention or behavior. Thus, the probability of a study not being published due to the non-confirmation of one or more predicted relationships is diminished.

4.2.4.2.4 Attenuation corrections

Even if two variables are perfectly correlated, the observed correlation of their measures will not be 1 in the presence of measurement error. This phenomenon, known as attenuation, is often corrected in meta-analyses to account for measurement error (Hunter & Schmidt, 2004; Valentine et al., 2022). To correct for measurement error, researchers must select a suitable reliability coefficient. Cronbach's alpha is the predominant measure of internal consistency reliability (McNeish, 2018). Therefore, Cronbach's alpha was employed as the reliability coefficient in this meta-analysis. However, not all studies included in this meta-analysis reported Cronbach's alpha values for all measures, making it impossible to correct the correlations on an individual study level. Instead, like other meta-analyses in consumer research (e.g., Hogueve et al., 2017), the

distribution of the reported Cronbach's alpha values was used (Hunter & Schmidt, 2004). On average, Cronbach's alpha values were consistently high for all measures ($>.8$). Correcting for measurement error using the distribution-based approach resulted in some non-positive definite meta-analytic correlation matrices at the individual study level. This issue arose because individual correlations exceeded 1 after the correction. To address this, these correlations were removed (Valentine et al., 2022). Table 2 [hier: Tabelle 10] presents the uncorrected results, whereas Table A1 [hier: Tabelle 13] (see Appendix) shows the corrected results. The corrected and uncorrected results are similar, aligning with the findings of Michel et al. (2011). Given the high average Cronbach's alpha values ($>.8$), this outcome was expected. Due to the aforementioned limitations regarding the loss of information from non-positive definite correlation matrices and the small impact of the correction, uncorrected correlations were used for further analyses, in line with Valentine et al. (2002).

4.2.4.2.5 Incorporating judgments on study quality

In the context of systematic reviews and meta-analyses, study quality can be defined as the extent to which the methods used to answer a research question align with the goals of the review (Valentine, 2019). Assessing study quality presents multiple challenges: First, study quality is always context-dependent. Second, study quality is a multidimensional construct. Therefore, attempting to assign a single number, score, or unitary judgment to assess the quality of a specific study is misguided (Valentine, 2019). Given these considerations, study quality was strictly assessed empirically (Valentine et al., 2022), using multiple indicators of publication medium quality as proxies for study quality and including them as moderators (see Chapter 4.2.2.7).

4.2.4.2.6 Moderation analysis in MASEM

As previously mentioned, among the various MASEM approaches, OSMASEM is the most versatile, as it can evaluate the effects of continuous and categorical moderators without creating subgroups (Jak & Cheung, 2022). As recommended by Jak and Cheung (2020), only one moderator was incorporated at a time in the model, and all continuous moderators were standardized to achieve convergence and more stable results. Moreover, switching behavior had to be excluded from the moderation analysis due to an insufficient amount of correlations, in line with the recommendations by Jak and Cheung (2020).

4.2.4.2.7 Effect size metric and conversion

As stated earlier, this meta-analysis used the correlation coefficient as the effect size metric. The formula proposed by Peterson and Brown (2005) was used to convert beta coefficients to correlation coefficients. Other effect size conversions were conducted using equations from Borenstein et al. (2021).

4.2.5 Conceptual framework

4.2.5.1 Independent and dependent variables

4.2.5.1.1 Dissatisfaction

Dissatisfaction refers to a psychological state that arises when consumers' experiences are coupled with disconfirmed expectations (Oliver, 1981). Satisfaction leads consumers to form repurchase intentions (Anderson & Sullivan, 1993) or continuation intentions (Bhattacharjee, 2001), while dissatisfaction deters them from future purchases or continued use. According to expectation-confirmation theory, consumers' intention to discontinue using a service is primarily determined by their dissatisfaction (Anderson & Sullivan, 1993; Oliver, 1980). Thus, it is predicted that dissatisfaction is positively related to switching intention (**H₁**).

4.2.5.1.2 Switching costs

Switching costs can be defined as consumers' perceived, anticipated, or experienced costs associated with switching from one alternative to another (Burnham et al., 2003; Jones et al., 2002). Switching costs include different types of costs, particularly financial, procedural, and relational costs, as well as combinations of these types (Burnham et al., 2003). In line with Pick and Eisend (2014), the focus of this meta-analysis is on overall switching costs. To explore how the results vary with different types of switching costs, a moderating variable that differentiates between monetary and non-monetary switching costs is included. Switching costs are seldom explicitly assessed but become salient when consumers face reasons to consider switching (Burnham et al., 2003). As such, switching costs can be considered barriers that discourage defection (Jones et al., 2000, 2002). Most researchers agree that switching costs reduce switching intention (e.g., Heide & Weiss, 1995; Morgan & Hunt, 1994; Wathne et al., 2001). Therefore, it is hypothesized that switching costs are negatively related to switching intention (**H₂**).

4.2.5.1.3 Alternative attractiveness

Alternative attractiveness refers to consumers' perceptions regarding the positive characteristics of competing alternatives (Bansal et al., 2005; Jones et al., 2000; Ping, 1993). A lack of alternative attractiveness encourages retention (Ping, 1993). On the other hand, when consumers perceive higher alternative attractiveness, the likelihood of switching increases as the perceived benefits of making a switch increase (Jones et al., 2000). Thus, it is hypothesized that alternative attractiveness is positively related to switching intention (**H₃**).

4.2.5.1.4 Switching intention and behavior

Switching intention can be defined as consumers' intention to switch between alternatives, whereas switching behavior refers to consumers' actual switching behavior (Ajzen, 1991; Bansal et al., 2005). Intentions are generally considered the best predictor of behavior (Ajzen, 1991). Therefore, it is predicted that switching intention is positively related to switching behavior (**H₄**).

4.2.5.2 Moderators

Several moderator variables are explored to explain the variation observed in the empirical studies included in this meta-analysis. While all moderators serve the statistical function of capturing variation in empirical findings (Brown et al., 1998), this study follows the approach of other meta-analyses (e.g., Okazaki et al., 2020; Lütjens et al., 2022) by categorizing them into two types: substantive moderators, which are directly related to the study's subject and for which hypotheses are proposed, and control moderators, which are used to adjust for potential methodological or study-related differences (Eisend, 2017; Lütjens et al., 2022).

4.2.5.2.1 Substantive moderators

4.2.5.2.1.1 Provider switch vs. technology switch

Research on consumers' service switching behavior using the PPM model can be broadly categorized into two distinct types: provider switching vs. technology switching. Grasping the differences between these two types of switching is essential for a comprehensive understanding of consumer switching behavior. Provider switching refers to a consumer's choice to switch from one service provider to another. Examples include switching between personal cloud storage services (e.g., Cheng et al., 2019) or mobile instant messaging services (e.g., Sun et al., 2017). The technology remains consistent in these instances, but the service provider changes. In contrast,

technology switching refers to a consumer's choice to switch from one technology to another. Examples include switching from cash payments to mobile payments (e.g., Hsieh, 2021) or from petrol cars to electric cars (e.g., Sajjad et al., 2020). In these instances, the technology changes, and the provider is irrelevant. A few studies investigated technology switching but also explicitly mentioned the different providers (e.g., Fang & Li, 2022). In these cases, the technology switch takes precedence. In many industries, providers offer similar core services (e.g., airlines, hair stylists, hotels), making it difficult for consumers to distinguish one as considerably more attractive than another. In contrast, the attractiveness of a new technology stands out more clearly from existing alternatives. Thus, it is hypothesized that the positive effect of alternative attractiveness on switching intention is weaker for provider switches than for technology switches (**H₅**).

4.2.5.2.1.2 Monetary switching costs vs. non-monetary switching costs

Additionally, similar to other meta-analyses in this field (e.g., Pick & Eisend, 2014), this analysis reveals another essential distinction regarding studies that included switching costs as a variable: monetary vs. non-monetary switching costs. Monetary switching costs refer to the loss of financially quantifiable resources (Burnham et al., 2003). Non-monetary costs refer to all perceived costs that cannot be quantified in financial or monetary terms and refer to psychological costs in terms of time and effort (Ping, 1993; Dick & Basu, 1994). Studies that did not include switching costs as a variable or did not provide adequate information to identify whether the switching costs were monetary or non-monetary were excluded from the analysis of this moderator. When switching entails monetary costs, the potential losses become more immediate and concrete for consumers. In line with the concept of loss aversion, this heightened focus on monetary losses likely increases switching costs and diminishes the attractiveness of the alternative (Kahneman & Tversky, 1979, 1984; Samuelson & Zeckhauser, 1988). Therefore, it is hypothesized that when switching costs are monetary, the negative effect of switching costs on switching intention is stronger (**H_{6a}**), and the positive effect of alternative attractiveness on switching intention is weaker (**H_{6b}**).

4.2.5.2.1.3 Contractual relation vs. non-contractual relation

Furthermore, a distinction is made between contractual and non-contractual relations. A contractual relation involves a formal agreement that establishes a recurring payment structure and outlines conditions for potential termination or breach. Examples include video streaming services, where

consumers pay annual or monthly subscription fees, and banking services, where consumers pay monthly fees and potential account closure fees in the event of a switch. In contrast, non-contractual relations, such as visiting a hair stylist or booking a hotel room, involve one-time transactions without ongoing contractual duties. Contractual relations create barriers that can elevate switching costs (Pick & Eisend, 2014). Moreover, consumers might experience a sense of obligation to uphold the contract (Pick & Eisend, 2014). Hence, consumers are likely to perceive higher switching costs in contractual relations, which makes them more reluctant to switch. Thus, it is hypothesized that when relations are contractual, the negative effect of switching costs on switching intention is stronger (**H₇**).

4.2.5.2.2 Control moderators

4.2.5.2.2.1 Student sample vs. non-student sample

Student samples are often more homogeneous than non-student samples (Agadullina & Lovakov, 2018). This sample homogeneity can affect the size of observed effects, as demonstrated by various meta-analyses (e.g., Brown & Stayman, 1992; De Matos & Rossi, 2008; Maseeh et al., 2021; Peterson, 2001). Furthermore, when considering student samples in the context of consumer switching behavior, it is important to recognize the unique demographic characteristics that distinguish students from non-student populations. Student samples typically consist of younger individuals predominantly engaged in their education rather than full-time employment. These unique characteristics suggest that students may respond differently to factors influencing consumer switching behavior. Numerous studies included in this meta-analysis (e.g., Chou et al., 2016) provide comprehensive details about their samples. This granularity enables the identification of samples that, while not exclusively composed of students, predominantly consist of this demographic. To attain a more balanced distribution in the analysis of this moderator, a distinction was also made between samples comprising mostly students and those that do not.

4.2.5.2.2.2 Information system vs. no information system

An information system (IS) can be defined as a set of interrelated components that collect (or retrieve), process, store, and distribute information (Laudon & Laudon, 2021). For many ISs (e.g., social networking services), switching can be relatively easy and inexpensive, with alternatives being as little as a mouse click away (Chen & Hitt, 2002). Thus, in the context of ISs, consumers might react differently to factors that influence switching behavior.

4.2.5.2.2.3 Tangible vs. intangible

In this study, all marketing offerings, both tangible and intangible, are considered as services, which are defined as the application of specialized competencies (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself (Vargo & Lusch, 2004a). This approach aligns with the service-dominant logic, recognizing that the traditional division between goods and services is outdated (Gummesson, 1995; Vargo & Lusch, 2004a; Vargo & Lusch, 2004b). Nevertheless, whether the switch is between tangible or intangible goods is included as a control moderator in this meta-analysis.

4.2.5.2.2.4 Age

Age is a common sociodemographic control variable in the studies included in this meta-analysis. Therefore, it is logical to include age as a moderator in this study. Specifically, the (approximated) median age was examined, as age was most commonly reported in intervals in the studies included in this meta-analysis (e.g., Mohd-Any et al., 2023), making it more accurate to approximate the median age rather than the mean age. Studies that provided no information on age were excluded from the analysis of this moderator.

4.2.5.2.2.5 Gender

Gender is also a common sociodemographic control variable in the studies included in this meta-analysis, making it straightforward to include as a moderator. Specifically, the percentage of males in each sample was examined. Studies that provided no information on gender were excluded from the analysis of this moderator.

4.2.5.2.2.6 Region

Previous meta-analyses in consumer research have examined region as a moderator (e.g., Lütjens et al., 2022). Therefore, the region in which a study was conducted was also included as a moderator in this study. The studies included in this meta-analysis provided enough information to identify geographical differences at the country level. However, due to the absence of sufficient observations at the country level, this moderator was categorized at the regional level, namely (1) Asia and (2) Other (including studies from America, Africa, and Europe), because most of the studies included in this meta-analysis were from Asia. If the region could not be determined, those studies were excluded from the analysis of this moderator.

4.2.5.2.2.7 Publication medium quality

Publication media have different standards of quality. High-quality publication media typically require more rigorous research designs than lower-quality ones, for example, by requiring designs with control variables, larger sample sizes, or more sophisticated analyses (Palmatier, 2016). Such factors that increase the quality of research can affect the findings of an empirical study (Lee & Baskerville, 2003) and thus influence meta-analytic results (e.g., Carrillat et al., 2018; Floyd et al., 2000). Therefore, whether a study was published in a journal, usually indicating a diligent peer-review process, or appeared in other formats, such as books, conference papers, master's or doctoral theses, and preprints, was assessed. Moreover, two measures of publication medium quality were included as moderators in this meta-analysis: (1) Scopus Cite Score from Harzing et al. (2022) and (2) Citations per document (2022, 4 years) from <https://www.scimagojr.com/>.

4.2.5.2.2.8 Hofstede's cultural dimensions

Research has shown that Hofstede's cultural dimensions effectively predict and explain consumption differences across various services (De Mooij & Hofstede, 2002). Furthermore, Hofstede's cultural dimensions (e.g., individualism) have proven to be important moderators in previous meta-analyses in consumer research (e.g., Pick & Eisend, 2014). Therefore, this meta-analysis also included Hofstede's six cultural dimensions as control moderators. Hofstede's cultural dimensions are particularly useful because data is readily available for many countries. The data was obtained from <https://www.hofstede-insights.com/country-comparison-tool>. If the country could not be determined, those studies were excluded from the analysis of this moderator.

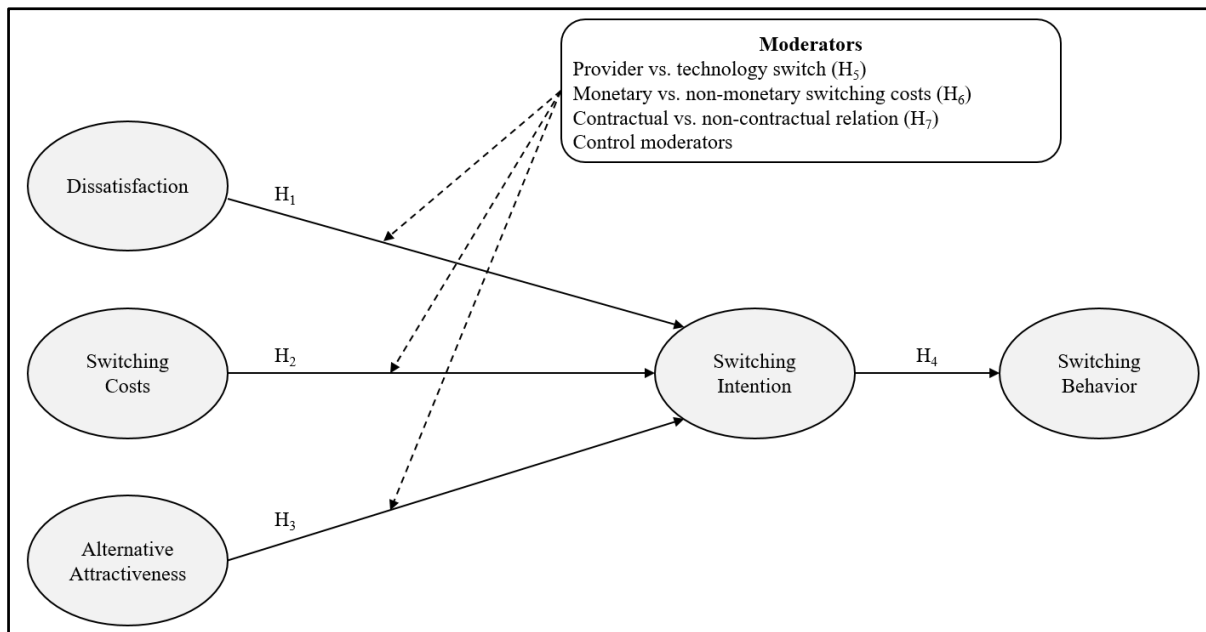


Abbildung 7: Conceptual framework

4.2.6 Results

4.2.6.1 Overview of PPM model studies

Among the 148 empirical PPM model studies on consumer service switching included in this meta-analysis, 382 different independent variables were used. Figure 2 [hier: Abbildung 8] shows the ten most frequently used independent variables (Switching Cost: 86, Alternative Attractiveness: 67, Dissatisfaction: 53, Habit: 27, Subjective Norm: 26, Service Quality: 25, Inertia: 20, Perceived Usefulness: 19, Perceived Risk: 19, Trust: 17) and their categorization into push, pull, or mooring factors.

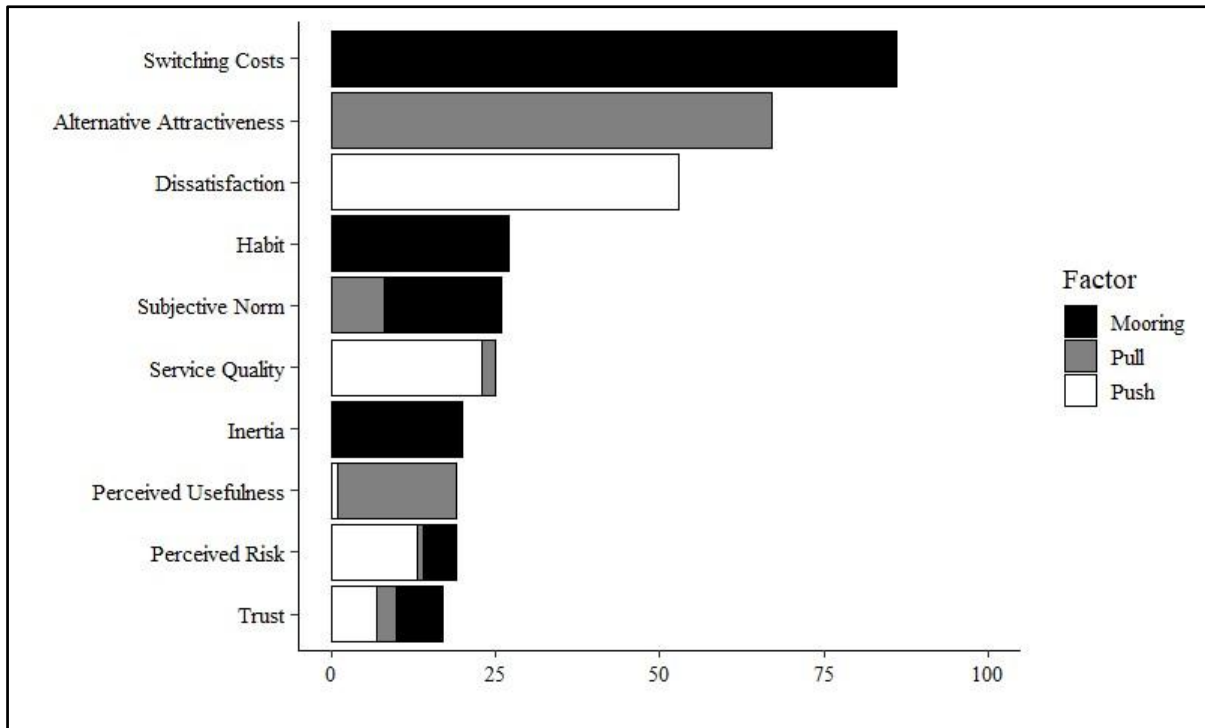


Abbildung 8: Most frequently used PPM variables

Furthermore, the investigated research contexts show considerable variety, with the three most commonly studied contexts being social networking services (9 studies), shopping channels (9 studies), and payment systems (9 studies). Other frequently studied contexts include financial services (7 studies), messaging services (6 studies), learning (6 studies), cloud services (6 studies), blogging (4 studies), accommodation services (4 studies), and delivery services (3 studies).

In terms of measurement, a total of 44 different sources were cited to measure dissatisfaction. The most frequently cited sources were Bhattacharjee (2001), with 11 citations, followed by Bansal et al. (2005) with 5 citations, and Sun et al. (2017) with 4 citations. Furthermore, a total of 51 different sources were cited to measure switching costs. The most frequently cited source was Bansal et al. (2005) with 12 citations, followed by Burnham et al. (2003) and Jones et al. (2000), each with 7 citations. To measure alternative attractiveness, a total of 43 different sources were cited. The most frequently cited source was Bansal et al. (2005), with 12 citations, followed by Hou et al. (2011), Jones et al. (2000), and Rezvani et al. (2015), each with 4 citations. Similarly, switching intention was measured citing 59 different sources. The most frequently cited source was Kim et al. (2006), with 18 citations, followed by Bansal et al. (2005) with 12 citations, and Jung et al. (2017) with 6 citations. Finally, switching behavior was measured citing 12 different sources. The most

frequently cited source was Bansal et al. (2005), with 5 citations, followed by Hsieh et al. (2012) with 3 citations. Overall, 152 unique sources were cited to measure these five variables. Table 3 [hier: Tabelle 8] shows the most frequently cited scales for each variable.

Scale	Items	Source
Dissatisfaction	How do you feel about your overall experience with [service]? very satisfied/very dissatisfied very pleased/very displeased very contented/very frustrated absolutely delighted/absolutely terrible	Bhattacharjee (2001)
Switching Costs	On the whole, I would spend a lot of time and money to switch from [service]. Generally speaking, the costs in time, money, effort, and grief to switch from [service] would be high. Overall, I would spend a lot and lose a lot if I switched from [service]. Considering everything, the costs to stop doing business with [service] and start up with a new [service] would be high.	Bansal et al. (2005)
Alternative Attractiveness	All in all, competitors would be much more fair than [service]. Overall, competitors' policies would benefit me much more than [service] policies. I would be much more satisfied with the services available from competitors than the service provided by my [service]. In general, I would be much more satisfied with competitors than I am with [service]. Overall, competitors would be better to do business with than [service].	Bansal et al. (2005)
Switching Intention	I am considering switching from my current [service]. The chance of my switching to another [service] is high. I am determined to switch to another [service].	Kim et al. (2006)
Switching Behavior	Did you switch your [service] in the past 2 months?	Bansal et al. (2005)

Tabelle 8: Most frequently cited measurement scales

Note. Dissatisfaction: 7-point semantic differential scale; the endpoints were reversed from the original to measure Dissatisfaction rather than Satisfaction, as is commonly done in PPM studies; Switching Costs, Alternative Attractiveness, Switching Intention: 7-point Likert scale ranging from strongly disagree to strongly agree; Switching Behavior: Yes/No; measured 2 months later than the other variables; [service] needs to be replaced depending on the research context

4.2.6.2 Descriptive statistics

Table 4 [hier: Tabelle 9] presents the descriptive results for the variables included in the conceptual framework. The large differences between the minimum and maximum correlations, the Q-statistics (Cochran, 1954), and the I^2 -statistics (Higgins et al., 2003) indicate high levels of heterogeneity in the data. If correlation coefficients in MASEM are heterogeneous across studies, applying a random-effects approach and conducting moderation analysis is recommended (Jak, 2015). Therefore, OSMASEM is a fitting choice for conducting further analysis (Jak & Cheung, 2022). Additionally, the statistical power of the combined set of studies was calculated for each relationship (Muncer et al., 2003). A value greater than .5 indicates that the meta-analysis has sufficient power to detect a meaningful effect size (Van Vaerenbergh et al., 2014), which holds true for all relationships except the one between alternative attractiveness and switching costs. Finally, the skewness statistic was calculated for each relationship to assess the symmetry of the distribution of correlation coefficients. A value within the range of -1 to +1 generally indicates an acceptable level of skewness (Hair et al., 2013), which holds true for all relationships.

	k	N	r	r _{min}	r _{max}	Q	I ²	Power	Skewness
DS ↔ SI	46	17,466	.334	-.190	.680	931.109**	95.167%	>.999	-.458
SC ↔ SI	74	25,779	-.143	-.715	.831	9692.828**	99.247%	>.999	.499
AA ↔ SI	53	20,138	.477	.060	.924	3948.301**	98.683%	>.999	.275
SI ↔ SB	15	5,978	.545	.124	.810	427.419**	96.724%	>.999	-.618
DS ↔ AA	18	7,477	.270	-.035	.646	473.803**	96.412%	>.999	.225
DS ↔ SC	30	10,913	.030	-.466	.685	1713.256**	98.307%	.879	.402
AA ↔ SC	28	9,296	.003	-.580	.852	4946.656**	99.454%	.057	.515

Tabelle 9: Descriptive statistics

Note. k: Number of correlations per relation, N: Total number of respondents across k samples, r: mean correlation, r_{min}: minimum correlation, r_{max}: maximum correlation, Q: Q-statistic, I²: I²-statistic, Power: Power test using N as sample size and $\alpha=.05$, * $p<.05$, ** $p<.01$

4.2.6.3 Main effects

Table 2 [hier: Tabelle 10] shows the results for the main effects of the conceptual framework. The overall model fit can be considered adequate based on fit indices ($\chi^2/d.f.=1.021$, $RMSEA=.001$, $SRMR=.078$, $TLI=.999$, $CFI=.999$). The results reveal that dissatisfaction ($\beta=.229$, $p<.001$, H₁) and alternative attractiveness ($\beta=.418$, $p<.001$, H₃) increase switching intention, which has a positive effect on switching behavior ($\beta=.557$, $p<.001$, H₄). Moreover, the results demonstrate that

switching costs decrease switching intention ($\beta=-.159, p<.001, H_2$). Thus, all hypotheses regarding the main effects can be confirmed.

Parameters	k	N	Estimate	Standard error	z value	p value
<i>Hypothesized paths:</i>						
DS → SI	46	17,466	.229	.036	6.429	<.001
SC → SI	74	25,779	-.159	.046	-3.480	<.001
AA → SI	53	20,138	.418	.032	12.855	<.001
SI → SB	15	5,978	.557	.045	12.253	<.001
<i>Correlations:</i>						
DS ↔ AA	18	7,477	.271	.046	5.889	<.001
DS ↔ SC	30	10,913	.030	.053	.556	.578
AA ↔ SC	28	9,296	.001	.060	.010	.992

Tabelle 10: OSMASEM results

Note. $R^2_{SI}=30\%$, $R^2_{SB}=31\%$, k: Number of correlations per relation, N: Total number of respondents across k samples, DS: Dissatisfaction, SC: Switching Costs, AA: Alternative Attractiveness, SI: Switching Intention, SB: Switching Behavior

Table A2 [hier: Tabelle 14] (see Appendix) reports the results for the main effects of the conceptual framework, excluding switching behavior. Since this model has zero degrees of freedom, the fit statistics are not informative. The results reveal only minimal variation in the parameter estimates. As previously mentioned, in line with recommendations by Jak and Cheung (2020), this model is used for the moderation analysis due to an insufficient number of correlations including switching behavior.

4.2.6.4 Moderation analysis

Table 5 [hier: Tabelle 11] displays the results of the moderation analysis. Provider switch vs. technology switch was assessed as a categorical moderator. The omnibus test indicates no significant effect overall ($\chi^2(3)=4.038, p=.257$). However, the individual moderating effects reveal that provider vs. technology switch significantly moderates the effect of alternative attractiveness on switching intention. Specifically, the coefficient equals $-.093$, meaning that, on average, the effect of alternative attractiveness on switching intention is $.093$ smaller for provider switches.

Similarly, monetary switching costs vs. non-monetary switching costs were assessed as a categorical moderator. The omnibus test again indicates no significant effect overall ($\chi^2(3)=5.442, p=.142$). Nevertheless, the individual moderating effects reveal that the effect of alternative attractiveness on switching intention is significantly moderated by monetary vs. non-monetary

switching costs. The coefficient equals $-.100$, which means that, on average, the effect of alternative attractiveness on switching intention is $.100$ smaller when monetary switching costs are present.

Furthermore, the moderation analysis examined contractual relation vs. non-contractual relation as a categorical moderator. Neither the omnibus test ($\chi^2(3)=2.040$, $p=.564$) nor the individual effects reveal significant findings.

Student sample vs. non-student sample was also assessed as a categorical moderator. The omnibus test indicates no significant effect overall ($\chi^2(3)=3.828$, $p=.281$), and the individual moderating effects show no significant effects.

Similarly, mostly student sample vs. not mostly student sample was assessed as a categorical moderator. The omnibus test reveals a significant effect overall ($\chi^2(3)=13.339$, $p=.004$). Furthermore, the individual moderating effects show that the effect of dissatisfaction on switching intention is significantly moderated by sample type. The coefficient is $.135$, which means that, on average, the effect of dissatisfaction on switching intention is $.135$ greater if the sample consists mostly of students. Moreover, the effect of switching costs on switching intention is significantly moderated by sample type. In detail, the coefficient is equal to $-.185$, meaning that, on average, the effect of switching costs on switching intention is $-.185$ smaller if the sample consists mostly of students. Considering the overall negative average effect of switching costs on switching intention, this reduction implies an intensification of the negative impact, suggesting a stronger negative influence of switching costs on switching intention if the sample consists mostly of students.

The moderation analysis also examined tangible vs. intangible as a categorical moderator. Neither the omnibus test ($\chi^2(3)=0.823$, $p=.844$) nor the individual effects show significant findings.

Moreover, IS vs. no IS was assessed as a categorical moderator. The omnibus test indicates a significant overall effect ($\chi^2(3)=8.808$, $p=.032$). Furthermore, the individual moderating effects demonstrate that the effect of dissatisfaction on switching intention is significantly moderated by IS vs. no IS. The coefficient is $.146$, which means that, on average, the effect of dissatisfaction on switching intention is $.146$ larger in the context of ISs.

Age (median, standardized) and gender (% male, standardized) were assessed as continuous moderators. For both variables, the omnibus tests show no significant effects overall (Age: $\chi^2(3)=2.919$, $p=.404$, Gender: $\chi^2(3)=1.523$, $p=.677$), and the individual moderating effects also indicate no significant findings.

Moderator	DS → SI	SC → SI	AA → SI
<i>Substantive moderators</i>			
Provider switch (N=49) vs. technology switch (N=51)	.024 (.055)	-.016 (.072)	-.093 (.045) *
Monetary switching costs (N=26) vs. non-monetary switching costs (N=46)	-.024 (.070)	-.093 (.075)	-.100 (.050) *
Contractual relation (N=14) vs. non-contractual relation (N=84)	-.094 (.083)	-.062 (.093)	.054 (.067)
<i>Control moderators</i>			
Student sample (N=13) vs. non-student sample (N=87)	.067 (.069)	-.127 (.086)	.031 (.081)
Mostly student sample (N=28) vs. not mostly student sample (N=72)	.135 (.055) *	-.185 (.070) **	-.031 (.050)
Tangible (N=10) vs. intangible (N=90)	-.052 (.109)	-.073 (.139)	-.040 (.076)
IS (N=81) vs. no IS (N=19)	.146 (.072) *	.143 (.103)	.095 (.061)
Age (N=89)	-.035 (.025)	-.008 (.035)	-.014 (.026)
Gender (N=98)	-.020 (.029)	.007 (.036)	-.019 (.029)
Asia (N=78) vs. other region (N=14)	-.012 (.069)	.095 (.086)	.067 (.081)
Journal (N=85) vs. no journal (N=15)	-.104 (.066)	.118 (.094)	.033 (.066)
Scopus Cite Score (N=35)	-.064 (.034)	-.048 (.049)	-.058 (.040)
Citations per document (N=88)	.001 (.026)	-.011 (.034)	-.014 (.024)
Power distance (N=92)	-.003 (.026)	.042 (.033)	.002 (.023)
Individualism (N=92)	.009 (.027)	-.032 (.032)	-.037 (.031)
Masculinity (N=92)	.018 (.026)	-.006 (.034)	.003 (.022)
Uncertainty avoidance (N=92)	-.027 (.026)	-.029 (.035)	.019 (.023)
Long-term orientation (N=92)	.002 (.032)	.004 (.034)	.020 (.030)
Indulgence (N=92)	.022 (.029)	-.009 (.034)	-.034 (.025)

Tabelle 11: OSMASEM moderation analysis results

Note. N: Number of samples, * $p < .05$, ** $p < .01$, DS: Dissatisfaction, SC: Switching Costs, AA: Alternative Attractiveness, SI: Switching Intention

Region (Asia vs. other) was assessed as a categorical moderator. The omnibus test shows no significant effect overall ($\chi^2(3)=1.824$, $p=.610$), and the individual moderating effects reveal no significant effects.

Similarly, journal vs. no journal was assessed as a categorical moderator. Neither the omnibus test ($\chi^2(3)=4.295$, $p=.231$) nor the individual effects suggest significant effects.

Scopus Cite Score (standardized) and citations per document (standardized) were assessed as continuous moderators. While the omnibus test for Scopus Cite Score ($\chi^2(3)=8.189$, $p=.042$) indicates a significant overall effect, the individual moderating effects reveal no significant

findings. For citations per document, neither the omnibus test ($\chi^2(3)=.399$, $p=.940$) nor the individual moderating effects show significant results.

Finally, Hofstede's six cultural dimensions (standardized) were assessed as continuous moderators. The omnibus tests suggest no significant effect overall (Power distance: $\chi^2(3)=1.688$, $p=.640$, Individualism: $\chi^2(3)=2.262$, $p=.520$, Masculinity: $\chi^2(3)=.651$, $p=.885$, Uncertainty avoidance: $\chi^2(3)=2.154$, $p=.541$, Long-term orientation: $\chi^2(3)=.488$, $p=.921$, Indulgence: $\chi^2(3)=2.024$, $p=.567$), and the individual moderating effects reveal no significant effects for any of the six dimensions.

Chapter 6 offers an interpretation of the results and discusses their theoretical and managerial implications.

4.2.7 Discussion and implications

Heterogeneity and resulting incomparability between PPM model studies are prevalent issues. After nearly two decades of research on the PPM model, this is the first study to provide a comprehensive overview and meta-analytical test of the PPM model to address this problem. The findings reveal several important theoretical (Chapter 6.1) and managerial implications (Chapter 6.2).

4.2.7.1 Theoretical implications

First, this study reveals widespread heterogeneity and resulting incomparability in the selection, categorization, and measurement of push, pull, and mooring variables. Among the 148 PPM model studies identified as eligible in the data collection process, 382 different independent variables were used. As shown in Figure 2 [hier: Abbildung 8], the three most frequently used and unequivocally categorizable variables within the top ten are dissatisfaction (push), alternative attractiveness (pull), and switching costs (mooring). Moreover, there is considerable heterogeneity in the measurement of these variables. Given that appropriate construct measurement is essential for the validity and comparability of research results, and that even small variations in measurement can have a significant impact, this finding is very concerning (Bergkvist & Langner, 2017). Thus, future research should use the conceptual framework, which includes dissatisfaction, alternative attractiveness, switching costs, switching intention, and switching behavior, as a baseline model for PPM model studies to enhance comparability. Additionally, the measurement of these variables should be harmonized by appropriately using the most frequently cited scales, as shown in Table 3

[hier: Tabelle 8]. The use of these scales is recommended not only due to their prevalent adoption in existing PPM model studies, but also because they demonstrate content validity, ensuring that the measurements accurately reflect the definitions of the corresponding variables (Bergkvist & Langner, 2017).

Second, the results emphasize the predictive power of the PPM model. Previously, anecdotal evidence suggested that the PPM model explained more variance in the dependent variables switching intention and switching behavior than comparable models. For example, Lim and Choi (2017) and Chang et al. (2014) examined switching intention in the context of social networks. Lim and Choi (2017) explained 37% of the variance in switching intention using a conceptual model based on the stressor-strain-outcome framework. In contrast, Chang et al. (2014) achieved a variance explanation of 58% using the PPM model. Similarly, Goode (2015) and Wu et al. (2017) investigated switching intention in the context of cloud storage services. Goode (2015), using a model based on the technology acceptance model, explained 49% of the variance in switching intention. Wu et al. (2017), using the PPM model, explained 59% of the variance, demonstrating the superior predictive power of the model. This study substantiates these findings with meta-analytical evidence: The model, which consists of only the three most frequently used PPM variables, explains 30% of the variance in switching intention and 31% of the variance in switching behavior (see Table 2 [hier: Tabelle 10]). Therefore, future PPM model studies should include dissatisfaction, alternative attractiveness, and switching costs as baseline independent variables. Implementing this recommendation should not only improve predictive capacity, but also reduce the previously mentioned prevailing arbitrariness and heterogeneity in selecting independent variables in PPM model studies. While this provides a strong foundation, researchers are encouraged to explore and evaluate the inclusion of additional independent variables to determine their ability to explain additional variance. The inclusion of affective variables (e.g., anxiety, regret, affective commitment) would be particularly interesting, as dissatisfaction, alternative attractiveness, and switching costs are cognitive variables.

Third, this study substantially advances the evaluation of nomological validity within the PPM literature. Nomological validity refers to the degree to which predictions in a formal theoretical network containing a construct of interest are confirmed (Bagozzi, 1981). In the context of nomological validity, it is advisable to conduct multiple replications of model tests across large samples to reduce the likelihood of encountering false positive results due to chance (Hagger et al.,

2017). Once sufficient evidence is available, these replications should be subjected to MASEM, which serves as a powerful tool to assess the collective evidence supporting a nomological network, while also correcting for methodological inadequacies (Hagger et al., 2016; Cheung & Hong, 2017). MASEM provides a rigorous test of nomological validity by drawing on the aggregated evidence from numerous replications. This approach is particularly robust because it is based on multiple replications and incorporates corrections for potential biases that could lead researchers to erroneous conclusions regarding the acceptance or rejection of the nomological network (Hagger et al., 2017). Currently, the PPM literature encompasses a substantial number of replications for the most commonly observed effects, but it lacks a comprehensive MASEM analysis. Consequently, this study is notably valuable in addressing this deficiency. In this regard, the unique contribution of this study relative to existing meta-analyses becomes clear. While there have been meta-analyses exploring specific relationships—such as Pick and Eisend (2014), who investigated the relationship between switching costs and switching—none have examined the comprehensive nomological network that encompasses dissatisfaction, alternative attractiveness, switching costs, switching intention, and switching behavior collectively. Moreover, this meta-analysis is distinct in that it only includes studies using the PPM model.

Fourth, the results show that dissatisfaction and alternative attractiveness positively influence switching intention, which increases switching behavior. Moreover, the results show that switching costs decrease switching intention. These effect directions align with expectations derived from theoretical considerations, confirming the hypotheses. Regarding effect sizes, the results show that switching intention exerts a large positive influence on switching behavior, alternative attractiveness exerts a large positive influence on switching intention, dissatisfaction exerts a medium positive influence on switching intention and switching costs exert a small negative influence on switching intention (Cohen, 1988). These findings provide a benchmark for future studies, offering reliable estimates of the true effect sizes. This helps researchers conduct a priori analyses, enabling them to calculate the necessary sample size based on the required significance level, the desired statistical power, and the to be detected effect size (Cohen, 1988). Additionally, by establishing these effect sizes, future research can move beyond merely confirming relationships and instead focus on exploring moderators and boundary conditions, thereby advancing theory development. The fact that alternative attractiveness exerts the largest influence on switching intention is congruent with migration research, as factors of the destination dominate the decision-

making process for geographical migration decisions (Walmsley et al., 1998). This is because the choice of a destination often precedes the decision to move, as a visit to the destination triggers a reassessment of the conditions at the place of origin (Stimson & Minnery, 1998).

Fifth, the findings reveal a significant effect of the first substantive moderator, provider vs. technology switch. Specifically, the positive effect of alternative attractiveness on switching intention is weaker for provider switches than for technology switches, confirming H₅. This finding suggests that consumers perceive switching between technologies as a more significant upgrade than switching between providers. Thus, researchers should differentiate between provider and technology switches in future studies, as this distinction enables the development of more precise theoretical frameworks, enhancing the predictive capacity of future research.

Sixth, the findings show a significant effect of the second substantive moderator, monetary vs. non-monetary switching costs. Concretely, the positive effect of alternative attractiveness on switching intention is weaker when switching costs are monetary, confirming H_{6b}. This finding suggests that consumers perceive alternatives as a less significant upgrade when switching costs are monetary. H_{6a} could not be confirmed, indicating no significant differences between monetary and non-monetary switching costs in their capacity to reduce switching intention. While unexpected, this finding aligns with previous meta-analytical evidence (Pick & Eisend, 2014).

Seventh, the findings show no significant effect of the third substantive moderator, contractual vs. non-contractual relation. Namely, the effect of switching costs on switching intention does not differ between contractual and non-contractual relations, rejecting H₇. As hypothesized, some consumers might experience heightened switching costs in contractual relations. However, others may anticipate and accept these costs from the outset, as they are predetermined in contractual relations, reducing the likelihood that these costs will influence future switching decisions (Pick & Eisend, 2014).

Eighth, the results indicate two significant effects of the control moderator, mostly student sample vs. not mostly student sample. Specifically, the positive effect of dissatisfaction on switching intention is stronger for samples consisting mostly of students, and switching costs have a stronger negative influence on switching intention if the sample consists mostly of students. Students tend to have more limited budgets, making switching costs (especially monetary) more significant for them. This heightened financial sensitivity could increase the negative impact of switching costs

on their switching intention. Moreover, dissatisfaction among students could more easily induce a reassessment of spending priorities, leading to increased switching intention.

Ninth, the results show a significant effect of the control moderator, IS vs. no IS. Concretely, the positive effect of dissatisfaction on switching intention is stronger in the context of IS. Research has shown that dissatisfaction is the primary reason users discontinue their incumbent IS (Parthasarathy & Bhattacharjee, 1998). ISs frequently involve rapidly evolving technologies, where user expectations are constantly increasing. Therefore, any perceived shortcomings may lead to increased dissatisfaction due to these high expectations and, thus, increased switching intention.

Finally, while no further significant moderating effects were identified at the individual level, the omnibus test of all three moderating effects reveals a significant overall effect for the Scopus Cite Score, an indicator of journal quality. A closer examination of the individual moderating effects that approached significance, together with the other indicators of publication medium quality, suggests that studies published in high-quality media tend to report smaller main effects than studies published in low-quality media. This finding is consistent with other meta-analyses in consumer research (e.g., Lütjens et al., 2022). One possible explanation is that high-quality media tend to require more rigorous research designs (Palmatier, 2016), which help minimize methodological deficiencies that can otherwise lead to exaggerated effect sizes (Fleming et al., 2014).

4.2.7.2 Managerial implications

Switching behavior in a business context inherently involves two entities: the one that loses a customer and the one that gains a customer. This dual nature of switching underlines that the managerial implications are always twofold, affecting both retention and acquisition strategies. This meta-analysis shows that companies can proactively motivate customers to switch by (1) demonstrating and communicating the benefits and competitive advantages of their service (alternative attractiveness), (2) highlighting the shortcomings of the competing service (dissatisfaction), and by (3) making it as easy and cheap as possible for customers to switch to their service (switching costs).

To enhance alternative attractiveness, companies should clearly demonstrate and communicate the unique benefits and competitive advantages of their offerings. This may include showcasing unique features, superior quality, or better pricing. Furthermore, freemium business models (Gu et al.,

2018) or offering free trials seem to be highly promising initiatives for companies, especially considering that, according to the results, alternative attractiveness exerts the strongest influence on switching intention. This is because when customers experience a service from a different company for the first time, it may cause them to reconsider the adequacy of their currently used service. To capitalize on dissatisfaction with the competing offers, companies should identify gaps in their competitors' offerings and position their services as solutions to these gaps. Finally, to reduce switching costs, effective strategies may include offering incentives to new customers, simplifying the switching process, reimbursing customers for financial expenses associated with switching (Bergel & Brock, 2018), and providing excellent customer support.

Furthermore, the findings illustrate the benefits of a combined marketing approach, aligning with insights from previous research (Chuah et al., 2017). Rather than focusing on just one of the determinants of switching behavior, companies should aim to address all of them simultaneously. For example, a retail bank could enhance its marketing communication by moving beyond a one-sided advertising message such as "Open a savings account with us and enjoy a 5% interest rate (alternative attractiveness)". Instead, a holistic advertising message could be "Open a savings account with us and enjoy a 5% interest rate (alternative attractiveness), significantly higher than the 2% interest rate offered by your current bank (dissatisfaction), and take advantage of our free account transfer service to ease the transition (switching costs)". In applying this, managers should acknowledge that customers vary widely in their responsiveness to marketing approaches, and that not all customers are equally advantageous to the company (Piha et al., 2015).

In addition to these recommendations, companies should also consider the impact of various moderators on the main effects, as outlined in Chapter 6.1 of this study. Understanding these factors can guide more nuanced and effective managerial decisions. For example, companies targeting students should prioritize the management of switching costs, as these play a particularly important role in influencing students' switching decisions. By tailoring their approaches to specific contexts, companies can more accurately address the unique challenges and opportunities presented by different customer segments and scenarios.

4.2.8 Limitations and future research

The results and implications of this meta-analysis should be considered in light of some important limitations, which also suggest new avenues for future research. First, as mentioned above, the

PPM model is a sound theoretical framework to include different predictor variables commonly associated with switching intention and behavior by categorizing them as push, pull, or mooring factors (Bansal et al., 2005). Given the wide range of predictor variables within the PPM literature (see Figure 2 [hier: Abbildung 8]), this meta-analysis focused on the three most commonly used variables due to methodological constraints. Future meta-analyses in this area could expand the model to include additional variables as the volume of relevant studies increases. Moreover, due to the methodological constraint of using correlation matrices as input and not having access to the underlying data, this meta-analysis was unable to model the interaction effects required to test switching costs as a moderator of the effects of dissatisfaction and alternative attractiveness on switching intention. According to migration research, mooring factors can moderate the relationships between push and pull factors and the migration decision (Lee, 1966), and their moderating role has been empirically demonstrated in service research by Bansal et al. (2005). Further investigation into the moderating role of mooring factors in future research would contribute to a more detailed understanding of switching and thus holds significant theoretical and managerial value.

Second, the number of PPM model studies examining actual switching behavior is relatively small, with most research focusing on switching intention due to the easier study design. The PPM literature would benefit greatly from more empirical results on actual switching behavior.

Third, the PPM model has been applied in various contexts, with some receiving more attention than others (see Chapter 5.1). The PPM literature would be enriched by additional studies in lesser-explored contexts.

Fourth, the accuracy of the meta-analytical results is affected by suboptimal methodological reporting in some of the included studies. Comprehensive reporting should particularly include a correlation matrix, a complete description of the sample, the measurement instruments used, their sources, and the reliability coefficients of these instruments. Moreover, as noted above, construct measurement differs across the studies included in this meta-analysis, affecting the accuracy of the results.

Theme	Future research directions
Improve comparability among PPM studies	Use dissatisfaction, alternative attractiveness, and switching costs as baseline independent variables to predict switching intention (and switching behavior).
	Use the most cited, valid measurement scales provided in this study (see Table 3 [hier: Tabelle 8]).
	When measuring other independent variables, provide the exact measurement scales that were used.
	In addition, reporting should include a correlation matrix, a complete description of the sample, the sources and the reliability coefficients of the measurement scales.
Expansion of PPM variables	Explore additional independent variables to determine their ability to explain more variance.
	The inclusion of affective variables (e.g., anxiety, regret, affective commitment) could be particularly interesting, as dissatisfaction, alternative attractiveness, and switching costs are cognitive variables.
	Moreover, the inclusion of context-specific variables (e.g., digital literacy in digital switching contexts) could be interesting and help to explain additional variance.
	When exploring additional independent variables, be sure to provide a sound theoretical argumentation of whether the variables are push, pull, or mooring variables.
Explore moderators	Table 5 ¹⁹ [hier: Tabelle 11] offers meta-analytical insights into the effects of study level moderators, providing explanations for differences in effect sizes. To further advance theory development, primary studies should investigate the effects of individual level moderators.
	Examine the role of mooring factors in moderating the relationships between push and pull factors and switching.
More studies on actual switching behavior	Conduct studies on actual switching behavior, as there is currently a lack of such studies, to improve practical relevance.
	In doing so, investigate variables that influence the intention-behavior gap (e.g., habit) to better understand why switching intention does not always result in actual switching behavior.
	When available, use objective data sources (e.g., transaction records, customer logs) to validate self-reported measures of switching behavior.
More studies in underexplored or new research contexts	Conduct more studies in underexplored or new consumer service switching research contexts (see Chapter 5.1) to enrich the PPM literature.
	Explore B2B switching contexts, where push, pull, and mooring factors, as well as their influence on switching, may differ significantly from those in consumer service switching.

Tabelle 12: Future research directions within themes

¹⁹ In der veröffentlichten Version des Beitrags wird an dieser Stelle versehentlich auf „Table 4“ verwiesen. Die korrekte Tabellenangabe lautet „Table 5“.

Finally, this meta-analysis is among the first in service research to use the OSMASEM approach developed by Jak and Cheung (2020). This new MASEM approach has several advantages over other methods (Jak & Cheung, 2022; Steinmetz & Block, 2022). Thus, it should be used more frequently in future meta-analyses when applicable. Table 6 [hier: Tabelle 12] outlines key research directions within themes for future PPM model studies.

4.2.9 Conclusion

The aim of this study was to address the prevailing heterogeneity and the resulting incomparability in the application of the PPM model and, based on this, to develop proposals to harmonize future research. Among the 148 PPM model studies identified as eligible in the data collection process, 382 different independent variables were used. The three most frequently used and unequivocally categorizable variables within the top ten are dissatisfaction (push), alternative attractiveness (pull), and switching costs (mooring). Moreover, considerable heterogeneity in the measurement of these variables was found. Through MASEM, dissatisfaction, alternative attractiveness, and switching costs were found to significantly influence switching intention, explaining 30% of the variance in switching intention, which explains 31% of the variance in switching behavior, thus making them well suited predictor variables in their intended domain. Additionally, these relationships are influenced by moderators, revealing interesting new insights for researchers and practitioners. Future research should use the conceptual framework, which includes dissatisfaction, alternative attractiveness, switching costs, switching intention, and switching behavior, as a baseline model for future PPM model studies to enhance comparability and achieve high predictive power. Additionally, the measurement of these variables should be harmonized by appropriately using the most frequently cited scales, as shown in Table 3 [hier: Tabelle 8].

4.2.10 Appendix

Parameters	k	N	Estimate	Standard error	z value	p value
<i>Hypothesized paths:</i>						
DS → SI	46	17,466	.235	.042	5.559	<.001
SC → SI	74	25,779	-.182	.054	-3.371	<.001
AA → SI	51	19,182	.457	.037	12.412	<.001
SI → SB	15	5,978	.638	.052	12.202	<.001
<i>Correlations:</i>						
DS ↔ AA	18	7,477	.307	.053	5.842	<.001
DS ↔ SC	30	10,913	.034	.060	.557	.578
AA ↔ SC	28	9,296	.001	.070	.016	.987

Tabelle 13: OSMASEM results with attenuation corrections

Note. $R^2_{SI}=36\%$, $R^2_{SB}=41\%$, k: Number of correlations per relation, N: Total number of respondents across k samples, DS: Dissatisfaction, SC: Switching Costs, AA: Alternative Attractiveness, SI: Switching Intention, SB: Switching Behavior

Parameters	k	N	Estimate	Standard error	z value	p value
<i>Hypothesized paths:</i>						
DS → SI	46	17,466	.227	.037	6.163	<.001
SC → SI	74	25,779	-.150	.046	-3.257	<.001
AA → SI	53	20,138	.416	.032	12.829	<.001
<i>Correlations:</i>						
DS ↔ AA	18	7,477	.271	.046	5.886	<.001
DS ↔ SC	30	10,913	.029	.053	.553	.580
AA ↔ SC	28	9,296	.001	.060	.015	.988

Tabelle 14: OSMASEM results without switching behavior

Note. $R^2_{SI}=30\%$, k: Number of correlations per relation, N: Total number of respondents across k samples, DS: Dissatisfaction, SC: Switching Costs, AA: Alternative Attractiveness, SI: Switching Intention

4.3 Beitrag 3: Drivers and barriers of switching to sustainable services: Empirical evidence from a two-wave study of sustainable search engines

Autoren	Tobias Marx
Zitation	-
URL	-
Keywords	Digital, Internet, Marketing research, Quantitative research, Relationship marketing, Satisfaction
Status	In Begutachtung (Revise & Resubmit, zur Wiedereinreichung in Vorbereitung)

Tabelle 15: Kurzübersicht zu Beitrag 3

Quelle: Eigene Darstellung

4.3.1 Abstract

Purpose: The rapid expansion of digital services, accelerated by artificial intelligence, is intensifying the environmental footprint of widely used services such as search engines. While environmentally sustainable alternatives exist, their adoption remains minimal. This study investigates what drives users to switch from conventional services to sustainable options, using search engines as the research context.

Design/methodology/approach: A two-wave online survey of German internet users captures both switching intention and behavior over a two-month period. The study builds on the push-pull-mooring (PPM) model, integrating established with novel, sustainability-specific predictors.

Findings: The pull factor, consisting of alternative attractiveness, subjective norm, perceived usefulness, and perceived environmental benefits, strongly drives switching, while the mooring factor, comprising switching costs, inertia, habit, perceived risk, and low consciousness for sustainable consumption, significantly hinders switching. Moreover, the mooring factor not only directly reduces switching intention but also mitigates the influence of the pull factor on switching intention, and weakens the relationship between switching intention and switching behavior. In contrast, the push factor has no significant effect on switching.

Originality: This study extends the PPM model to sustainable service contexts, offering rare evidence on actual switching behavior and highlighting the importance of addressing personal barriers alongside promoting the appeal of sustainable alternatives.

4.3.2 Introduction

Search engines, a fundamental part of today's digital infrastructure (Lewandowski et al., 2023), serve as a prime example of both the possibilities and challenges of environmental sustainability in digital services. Google, which dominates the search engine space with a 91.38% market share in Europe as of March 2024 (Bianchi, 2024), has seen its environmental impact surge: In 2023, Google's greenhouse gas emissions rose to 14.30 million metric tons of carbon dioxide equivalent—a 48% increase over the past five years (Milmo, 2024). This significant increase is largely attributed to the energy demands of Google's data centers, which are intensifying with the integration of artificial intelligence (AI) into its products, including AI-enhanced search features (Kerr, 2024). Research suggests that a standard Google search consumes approximately .3 Wh of electricity, whereas an AI-powered Google search may use up to 8.9 Wh per request—nearly 30 times more energy (de Vries, 2023). Although Google has set the goal to achieve net-zero emissions by 2030, it acknowledges considerable challenges in reaching this target, especially given the growing environmental impact of advancing AI technologies (Milmo, 2024). In contrast, environmentally sustainable search engines with comparable search performance are available (Ragobert, 2022). For instance, Ecosia, a search engine with a mere .29% share of the European market as of October 2024 (Bianchi, 2024), has embraced sustainability from its inception. Unlike Google, Ecosia operates with real-zero emissions, running entirely on renewable energy, and channels all its profits into climate action initiatives, such as global reforestation projects (Gottlieb, 2021).

Prior research indicates that users are aware of differences in search engines' environmental impact (Ruch et al., 2012). While other criteria such as result quality and speed tend to play a more dominant role in search engine choice, a search engine's environmental sustainability is also considered an important criterion—particularly among environmentally oriented users (Ruch et al., 2012). Nonetheless, the market share of environmentally sustainable search engines remains marginal, underscoring the broader challenge of understanding consumers' switching intention and behavior toward sustainable services. Against this background, this study investigates the

determinants of internet users' switching intention and behavior toward environmentally sustainable search engines.

To achieve that, this study applies the push-pull-mooring (PPM) model, which is an established framework in the literature for explaining service switching intention and behavior (Bansal et al., 2005; Marx, 2025). In applying the PPM model, this study provides numerous contributions to the literature. First, it expands the theoretical scope of the PPM model by introducing novel, context-specific variables. Specifically, this study examines perceived environmental threats of the status quo (push), perceived environmental benefits of the alternative (pull), and low consciousness for sustainable consumption (mooring). These variables, which have been barely or not at all explored in prior PPM model studies, are theoretically grounded as push, pull, and mooring factors, respectively. Their inclusion enriches the model's explanatory power. Second, it contributes toward improving the comparability of PPM model studies by incorporating the most frequently used PPM variables and by utilizing frequently cited, valid measurement scales identified in a recent meta-analytical review on the PPM model (Marx, 2025). Third, this study deepens the understanding of the mooring factor by examining its multifaceted role in the switching process, in particular its moderating effect not only on the relationships between the push and pull factor and switching intention but also on the relationship between switching intention and switching behavior. Based on the existing body of literature, this is the first PPM model study to investigate this extended moderating role, providing novel insights into the intention-behavior gap in the context of switching. Fourth, this study addresses the lack of research on actual switching behavior (Marx, 2025) by including self-reported behavioral data collected two months after the initial survey. This rare focus on actual behavior enhances the practical relevance of the findings. Finally, it contributes to the growing literature on sustainable services by showing how consumers balance environmental considerations with functional and personal barriers when deciding whether to switch. Specifically, this study addresses the following research question: *What factors determine internet users' switching intention and behavior toward environmentally sustainable search engines?*

To answer this question, the rest of this paper is organized as follows: Chapter 2 reviews the literature background. Chapter 3 outlines the methodological approach. Chapter 4 presents the results. Lastly, Chapter 5 discusses the findings, highlighting their theoretical and managerial relevance as well as the study's limitations and avenues for further research.

4.3.3 Literature background

4.3.3.1 Push-pull-mooring model

The push-pull-mooring (PPM) model, initially developed in migration research (Bogue, 1969; Lee, 1966; Moon, 1995; Ravenstein, 1885), provides a theoretical framework for understanding why individuals relocate from their place of origin to a new destination. The model consists of three key components: the push factor, the pull factor, and the mooring factor. The push factor motivates individuals to leave their current location (Stimson and Minnery, 1998), while the pull factor attracts them to a new destination (Moon, 1995). The mooring factor, including both personal and social elements, can either anchor individuals to their place of origin or facilitate their migration to a new location (Moon, 1995).

Bansal et al. (2005) were the first to apply the PPM model in service research, demonstrating its strong predictive power for switching intention and behavior. Since then, the PPM model has been applied in various service contexts (Marx, 2025), making it an established framework in the services marketing literature for explaining why consumers switch.

4.3.3.2 Hypotheses development

4.3.3.2.1 Push factor

In the context of this study, the push factor motivates users to switch from their current primary search engine to the environmentally sustainable alternative Ecosia. To operationalize the push factor in this study, the three most commonly used push variables from the literature—dissatisfaction, bad service quality, and distrust—are incorporated, along with the context-specific variable perceived environmental threats.

Dissatisfaction can be defined as a psychological state that occurs when consumers' experiences do not meet their expectations (Oliver, 1981). While satisfaction leads consumers to develop continuation intentions (Bhattacharjee, 2001), dissatisfaction discourages them from continued use (Bolfing, 1989). In the context of search engines, dissatisfied users are likely to stop using their incumbent search engine and switch to an alternative. Empirical evidence for the positive relationship between dissatisfaction and switching intention is provided, for example, by Kim and Han (2023) as well as Ye and Potter (2011).

For the purpose of this study, bad service quality can be defined as the user's overall impression of the relative inferiority of a particular search engine (Bitner and Hubbert, 1994). Perceived poor service quality experiences result in negative behavioral intentions toward companies, including switching to competitors (Zeithaml et al., 1996). Moreover, Matt et al. (2015) provide empirical evidence supporting a positive relationship between bad service quality and switching intention.

Distrust can be defined as the expectations held by a consumer that the service provider is unreliable and cannot be depended on to deliver on its promises (Sirdeshmukh et al., 2002). When consumers distrust a service provider, they are more likely to consider alternative providers (Jung et al., 2017). Empirical evidence for the positive relationship between distrust and switching intention is provided, for example, by Matt et al. (2015).

In this study, perceived environmental threats can be defined as the degree to which a person believes that using a particular search engine has negative environmental consequences (Wang et al., 2020). When individuals perceive using a particular search engine as a threat to the environment, this perception can trigger a protective response, increasing their likelihood of switching to an environmentally sustainable search engine (Wang et al., 2020). Empirical evidence for the positive relationship between perceived environmental threats and switching intention is provided, for example, by Wang et al. (2020) in the context of green transportation.

Overall, it is hypothesized that the push factor, operationalized by dissatisfaction, bad service quality, distrust, and perceived environmental threats, positively influences switching intention (**H₁**).

4.3.3.2.2 Pull factor

In the context of this study, the pull factor attracts users to switch toward the environmentally sustainable alternative Ecosia. To operationalize the pull factor in this study, the three most commonly used pull variables from the literature—alternative attractiveness, subjective norm, and perceived usefulness—are included, along with the context-specific variable perceived environmental benefits.

Alternative attractiveness refers to consumers' perceptions regarding the positive characteristics of competing alternatives (Bansal et al., 2005; Jones et al., 2000). High alternative attractiveness increases the likelihood of switching as the perceived benefits of making a switch increase (Jones et al., 2000). Empirical evidence for the positive relationship between alternative attractiveness and

switching intention is provided, for example, by Chang et al. (2014) in the context of social networking services.

Subjective norm refers to an individual's perceived social pressure to perform or not to perform a certain behavior (Ajzen, 1991). This perceived social pressure arises from whether the individual's important others approve or disapprove of the behavior (Ajzen, 1991). Depending on whether the behavior is switching to an alternative or staying with the incumbent, subjective norm can be modeled as either a pull factor or a mooring factor within the PPM model. In this study, subjective norm is modeled as a pull factor because the behavior in question is switching toward an environmentally sustainable search engine, which implies a positive influence on switching intention. Within the PPM model literature, there are numerous studies providing empirical evidence for the positive relationship between subjective norm and switching intention (e.g., Chen et al., 2023; Liao et al., 2021).

Within this study, perceived usefulness can be defined as the degree to which a person believes that using a particular search engine would enhance their search performance (Davis, 1989). When users perceive an alternative system as more useful than their current one, the potential benefits of making a switch increase. Numerous PPM model studies have shown that the perceived usefulness of the alternative is a strong determinant of switching intention (e.g., Lenz et al., 2023).

For the purpose of this study, perceived environmental benefits can be defined as the degree to which a person believes that using a particular search engine positively impacts the environment (Hazen et al., 2017). Prior research suggests that perceived environmental benefits associated with a product will typically affect consumer adoption, willingness to pay, and perception (Michaud and Llerena, 2011). Within the PPM model literature, Hazen et al. (2017) provide empirical evidence for the positive relationship between perceived environmental benefits and switching intention.

Overall, it is hypothesized that the pull factor, operationalized by alternative attractiveness, subjective norm, perceived usefulness, and perceived environmental benefits, positively influences switching intention (**H₂**).

4.3.3.2.3 Mooring factor

In the context of this study, the mooring factor consists of personal elements that anchor users to their current primary search engine. To operationalize the mooring factor in this study, the four most commonly used mooring variables from the literature—switching costs, inertia, habit, and

perceived risk—are used, along with the context-specific variable low consciousness for sustainable consumption.

Switching costs can be defined as users' perceived, anticipated, or experienced costs associated with switching from one alternative to another (Burnham et al., 2003; Jones et al., 2002). Thus, they can be understood as obstacles to switching (Jones et al., 2000; 2002). In the context of search engines, procedural switching costs, which refer to the expenditure of time and effort when switching (Burnham et al., 2003), are particularly relevant. Within the PPM model literature, there are numerous studies providing empirical evidence for the negative relationship between switching costs and switching intention (e.g., Chang et al., 2014; Lin and Huang, 2014).

Polites and Karahanna (2012) define inertia as user attachment to, and persistence in, using an incumbent system (i.e., the status quo), even if there are better alternatives or incentives to change. They conceptualize inertia as a second-order formative, first-order reflective multidimensional construct, consisting of an affective, a behavioral, and a cognitive dimension (Polites and Karahanna, 2012). Inertia leads users to perceive the relative benefits and ease of use of a new system as lower than the currently used system, which negatively affects their intention to adopt the alternative system (Polites and Karahanna, 2012). Empirical evidence for the negative relationship between inertia and switching intention is provided, for example, by Gray et al. (2017) and Kuo (2020).

Unlike inertia, habit can be defined as a learned response that is automatically triggered by certain stimuli in an individual's environment (Polites and Karahanna, 2013). Individuals will continue their habitual behavior unless a significant change in circumstances triggers the need for reassessment (Petty and Cacioppo, 1981; Polites and Karahanna, 2013). Thus, in the context of search engines, users who are already accustomed to using their incumbent search engine are less likely to carefully consider alternative search engines and their benefits. Within the PPM model literature, there are numerous studies providing empirical evidence for the negative relationship between habit and switching intention (e.g., Cheng et al., 2019; Tsai, 2023).

In this study, perceived risk refers to the subjective expectation of a loss associated with switching search engines (Sweeney et al., 1999). Perceived risk has been identified as a key variable explaining why users may resist adopting services (Lee, 2009). Within the PPM model literature,

Chen et al. (2023) provide empirical evidence for the negative relationship between perceived risk and switching intention.

Low consciousness for sustainable consumption can be defined as a lack of intention to consume in a way that enhances the environmental, social and economic aspects of quality of life (Balderjahn et al., 2013). In this study, in line with the context-specific push and pull variables—perceived environmental threats and benefits—the focus is placed solely on the environmental dimension. Prior research has shown that consciousness for sustainable consumption positively influences the intention to purchase sustainable products (Montreuil Carmona et al., 2024). To date, no PPM model study has investigated the role of consciousness for sustainable consumption in influencing switching intention.

Overall, it is hypothesized that the mooring factor, operationalized by switching costs, inertia, habit, perceived risk, and low consciousness for sustainable consumption, negatively influences switching intention (**H₃**).

According to migration research, the mooring factor can moderate the relationships between the push and pull factors and the migration decision (Lee, 1966). More specifically, Lee (1966) argues that even when individuals face strong push or pull factors, their decision to migrate ultimately depends on whether these factors are sufficient to overcome the mooring factor. Building on this, numerous studies applying the PPM model in a service switching context have explored these moderating effects, with mixed results regarding their statistical significance. For instance, Jung et al. (2017) and Matt et al. (2015) consistently found a significant interaction effect between the pull factor and the mooring factor but not between the push factor and the mooring factor. In contrast, Lai and Wang (2015) and Bansal et al. (2005) reported a significant interaction effect between the push factor and the mooring factor but not between the pull factor and the mooring factor. Notably, Chen and Keng (2019) found significant interaction effects between both the pull factor and the mooring factor as well as the push factor and the mooring factor. In the context of this study, mooring variables such as inertia, habit, or perceived switching costs may inhibit users from acting on push or pull variables—such as perceived environmental threats or alternative attractiveness—thereby preventing them from switching to a different search engine. It is thus expected that—even if the push and pull factors are strong—a user may remain with the current search engine when the mooring factor is strong. Therefore, it is hypothesized that the mooring factor weakens the positive

relationship between the push factor and switching intention (**H₄**), as well as the positive relationship between the pull factor and switching intention (**H₅**).

4.3.3.2.4 Switching intention and behavior

Generally, behavioral intentions can be defined as self-instructions to perform particular actions directed toward attaining a desired outcome (Sheeran and Webb, 2016) and are considered the best predictor of actual behavior (Ajzen, 1991). In the context of this study, switching intention refers to a user's intention to switch between search engines, whereas switching behavior refers to a user's actual search engine switching behavior (Ajzen, 1991; Bansal et al., 2005). Numerous PPM model studies provide empirical evidence for the positive relationship between switching intention and behavior (e.g., Bansal et al., 2005; Ye and Potter, 2011). Moreover, a recent meta-analysis on the PPM model confirms the strong positive impact of switching intention on behavior (Marx, 2025). Thus, it is hypothesized that switching intention increases switching behavior (**H₆**).

However, research has consistently shown that intention does not always translate into behavior (e.g., Fife-Schaw et al., 2007). This discrepancy, known as the intention-behavior gap, primarily arises from individuals who intend to change their behavior but fail to do so (Sheeran, 2002; Orbell and Sheeran, 1998). Researchers have sought to explain the intention-behavior gap, with one approach being the investigation of moderators (Sheeran and Webb, 2016). In the context of this study, it is expected that when the mooring factor is strong, a user may not actually switch search engines, even if their switching intention is strong. The mooring factor, operationalized by switching costs, inertia, habit, perceived risk, and low consciousness for sustainable consumption, imposes significant barriers that make it challenging for users to act on their switching intentions. Therefore, it is hypothesized that the mooring factor weakens the positive relationship between switching intention and switching behavior (**H₇**). The full conceptual framework is presented in Figure 1 [hier: Abbildung 9].

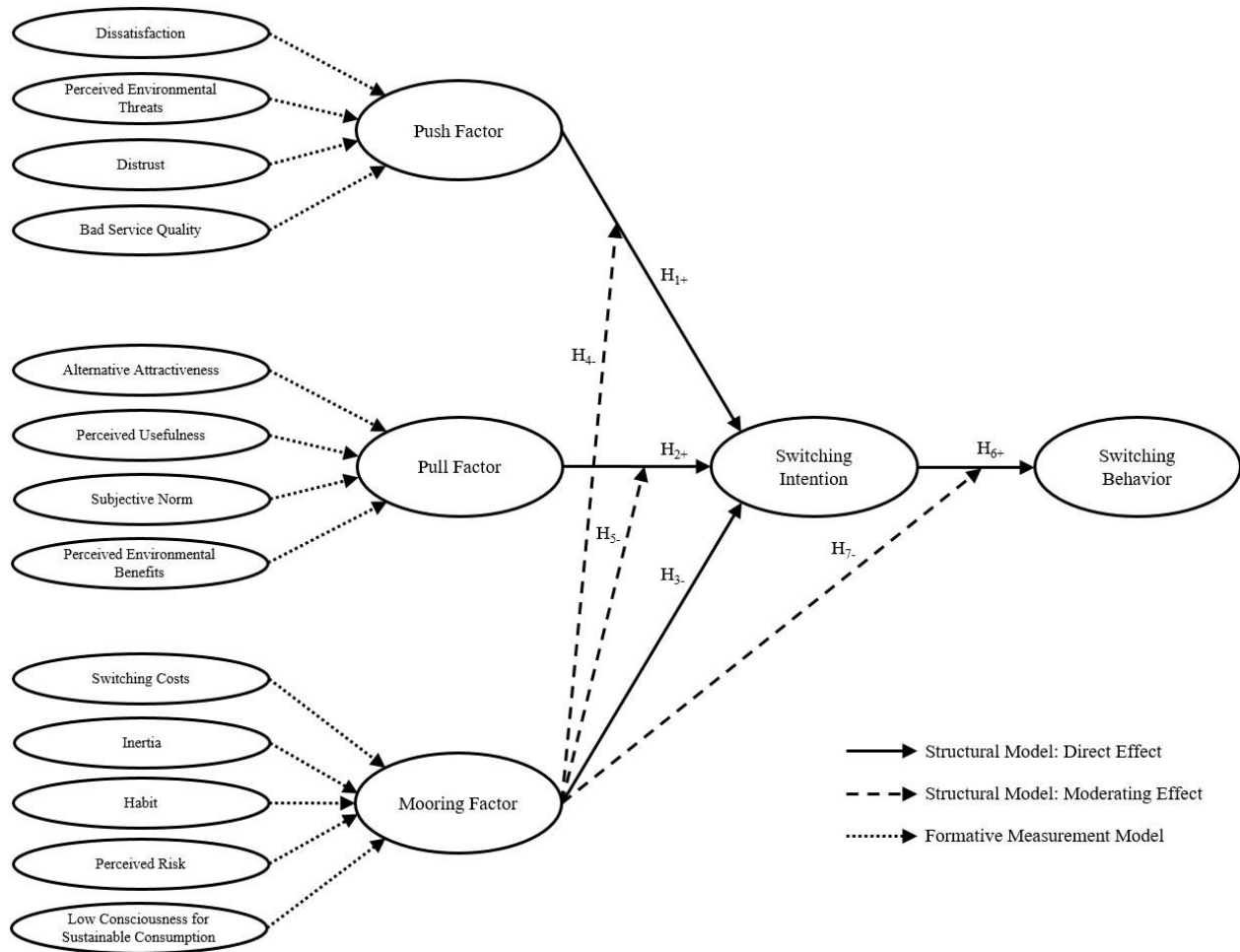


Abbildung 9: Conceptual framework

4.3.4 Method

4.3.4.1 Variable selection

A core issue in PPM model studies is the lack of comparability caused by arbitrary variable selection. A recent meta-analysis highlights this problem, revealing that the 148 PPM model studies analyzed used 382 distinct variables to operationalize the push, pull, and mooring factors (Marx, 2025). In response, this study adopts the ten most frequently used PPM variables as a baseline framework and, as recommended, integrates specific variables tailored to the context of this study to explain additional variance (Marx, 2025). Where the conceptualization of a variable was unambiguous (e.g., dissatisfaction as a push variable), it was adopted accordingly. In ambiguous cases, variables were categorized as push, pull, or mooring based on their best theoretical fit in this context.

4.3.4.2 Conceptualization of the push, pull, and mooring factors

Another key issue in PPM model studies lies in the conceptualization of the push, pull, and mooring factors. Bansal et al. (2005), in their seminal application of the PPM model to service research, conceptualized these factors as reflective-reflective second-order constructs (Sarstedt et al., 2019), consisting of lower-order subdimensions such as switching costs and subjective norm. Their findings demonstrated that the model with higher-order constructs explained more variance in switching intention compared to a direct-effects model. However, only 32% of PPM model studies employ the second-order construct model, while the remaining 68% use the direct-effects model (Marx, 2025). Moreover, among the studies adopting the second-order model, inconsistencies in conceptualization persist. For instance, Ye and Potter (2011) modeled the push, pull, and mooring factors as reflective-formative second-order constructs, deviating from the reflective-reflective approach of Bansal et al. (2005). In this study, it is argued that Ye and Potter's (2011) reflective-formative approach is more appropriate, and that the push, pull, and mooring factors are best conceptualized as formative constructs. For example, individuals are pushed away from their current service provider because they are dissatisfied, not vice versa. The indicator (dissatisfaction) causes the construct (push), supporting a formative conceptualization.

4.3.4.3 Survey design

To evaluate the proposed conceptual framework, a two-wave online survey was developed. Participants were recruited from the crowd-working platform Clickworker. In the first survey, participants were given an overview of the study's procedure, followed by a brief introduction to search engines. They were then asked to select the search engines they were aware of from a list of different search engines (e.g., Google, Bing). Thereafter, participants were asked to choose their primary search engine, described as the search engine they most frequently use for their personal internet searches. When applicable, the online survey customized all subsequent questions with the name of the selected search engine. Additionally, participants were asked to provide a percentage breakdown of their usage of the search engines they were aware of. Participants were then presented with a brief introduction to the search engine Ecosia. Subsequently, the dependent variable, switching intention, the independent variables, and sociodemographic variables were measured. To ensure high data quality, the first survey included the attitude toward the color blue marker variable (Miller and Simmering, 2023), the gamma factor scale of socially desirable

response behavior (Nießen et al., 2019), as well as three methodologically different attention checks that were built into the survey at different stages (Aguinis et al., 2021). Two months after completing the first survey, participants were invited to answer the second survey. In the second survey, participants were once again asked to select the search engines they were aware of and to provide an updated percentage breakdown of their usage of different search engines.

4.3.4.4 Measurement

For all latent variables within the conceptual framework, validated multi-item scales from prior research were employed. These measurements utilized either seven-point agree-disagree rating scales ranging from 1 to 7 or seven-point semantic differential scales ranging from -3 to 3 (Balderjahn et al., 2013: Consciousness for sustainable consumption; Bansal et al., 2005: Switching intention, alternative attractiveness, switching costs; Bhattacharjee, 2001: Satisfaction; Davis, 1989: Perceived usefulness; Hazen et al., 2017: Perceived environmental benefits; Limayem et al., 2007: Habit; Polites and Karahanna, 2012: Inertia; Sirdeshmukh et al., 2002: Trust; Sweeney et al., 1999: Perceived risk; Taylor and Baker, 1994: Service quality; Taylor and Todd, 1995: Subjective norm; Wang et al., 2020: Perceived environmental threats). In line with Ye and Potter (2011), switching behavior towards sustainable search engines was measured by calculating the change in Ecosia's usage percentage between the two surveys. For the data analysis, satisfaction was reverse-coded to measure dissatisfaction, service quality to measure poor service quality, and trust to measure distrust. This approach aligns with the conceptualization of push factors in migration research as variables that motivate individuals to leave their current location (Stimson and Minnery, 1998), meaning they should have a positive effect on switching intention. Furthermore, consciousness for sustainable consumption was reverse-coded to measure low consciousness for sustainable consumption, ensuring consistency with the other mooring variables in this study. This approach aligns with Bansal et al. (2005) by ensuring that all mooring variables represent inhibitors that prevent individuals from switching.

4.3.4.5 Pretest

To circumvent potential comprehension issues and survey functionality problems, a cognitive pretest was first conducted with five participants using the think-aloud method (Charters, 2003), in which participants were asked to verbalize their thoughts while completing the survey. Thereafter, a quantitative pretest was carried out. Before analyzing the data, participants who failed at least

one of the methodologically different attention checks that were built into the survey at different stages were removed (Aguinis et al., 2021). Moreover, participants were excluded based on their completion time for the survey, using a relative speed index of 2 as the maximum threshold (Leiner, 2019). Finally, participants with the most extreme scores on the gamma factor scale of socially desirable response behavior, which indicates a tendency to diminish negative qualities and overemphasize positive qualities (Nießen et al., 2019), were removed, resulting in a sample of 30 participants ($M_{age}=45.77$, $SD_{age}=12.50$, 60% female). For all multi-item scales, Cronbach's alpha, standardized factor loadings and average variance extracted (AVE) were assessed. The results revealed adequate reliability and validity.

4.3.4.6 Main study

A total of 400 German participants were recruited for the survey through Clickworker. The same data cleaning process outlined in Chapter 3.5 was applied, which resulted in a sample of 376 participants ($M_{age}=41.84$, $SD_{age}=11.72$, 41.22% female). These 376 participants were invited to complete the second survey two months later. Of these, 225 participants ($M_{age}=43.15$, $SD_{age}=11.71$, 41.78% female) completed the second survey, yielding a response rate of 59.84%. Among these 225 participants, 190 reported no change in their Ecosia usage percentage (84.44%), while 24 participants increased their usage percentage (10.67%) and 11 participants decreased it (4.89%). As respondents who completed both surveys did not differ demographically from those who only completed the first survey, following Ye and Potter (2011), non-response bias is not considered a concern.

4.3.5 Results

4.3.5.1 Preliminary considerations

Recently, the appropriate use of partial least squares structural equation modeling (PLS-SEM) has been the subject of methodological debate (Evermann and Rönkkö, 2023a; 2023b). Critics argue that the PLS-SEM algorithm produces biased estimates and provides no clear advantage over regression using simple, unweighted sums of indicators, and therefore favor either the simpler unweighted approach, or the use of covariance-based structural equation modeling (CB-SEM) instead (Rönkkö et al., 2022; Evermann and Rönkkö, 2023a). Advocates of PLS-SEM claim that its known bias is an intentional design choice rooted in the bias-variance tradeoff aimed at improving predictive performance (Sharma et al., 2023). They argue that this tradeoff enables

stronger out-of-sample prediction (Shmueli et al., 2016), with simulation studies showing that the bias is typically small and unlikely to pose practical concerns (Reinartz et al., 2009; Sarstedt et al., 2016).

In line with prior research (e.g., Menidjel et al., 2023), PLS-SEM was chosen over CB-SEM in this study because the model includes multiple formative higher-order constructs, for which PLS-SEM is the recommended approach (Hair et al., 2021). The following analyses were conducted using PLS-SEM in R (version 4.4.3) with the *sempr* package (version 2.3.4), primarily following the guidelines by Hair et al. (2021). Moreover, recent recommendations on the appropriate use of PLS-SEM, including an implicit call for more transparent reporting, were followed (Evermann and Rönkkö, 2023b).

4.3.5.2 Measurement model assessment

The first step in evaluating reflective measurement models (specified in *sempr* as composites using mode A, i.e., correlation weights) in PLS-SEM is to examine indicator loadings, with values above the recommended threshold of .708 indicating that the construct explains more than 50% of the indicator's variance (Hair et al., 2021). This threshold was met for all indicators except the first of habit, the first of affective inertia, the sixth of perceived usefulness, and the third and fourth of distrust, which were removed from further analysis. The second step assesses internal consistency reliability, typically using composite reliability and Cronbach's alpha, with the latter preferred for its conservatism (Hair et al., 2021). All Cronbach's alpha values exceeded the .7 threshold (Hair et al., 2021). The third step evaluates convergent validity using the average variance extracted (AVE). All AVE values exceeded the recommended .5 cutoff (Hair et al., 2021). Finally, the fourth step assesses discriminant validity to confirm that each construct is empirically distinct, using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) of correlations. The square roots of the AVE surpassed interconstruct correlations, meeting the Fornell-Larcker criterion requirement, and all HTMT values were below .85, satisfying this criterion as well (Hair et al., 2021). Table I [hier: Tabelle 16] displays Cronbach's alpha, AVE, and the Fornell-Larcker criterion for all constructs.

To evaluate the formative measurement model (specified in *sempr* as composites using mode B, i.e., regression weights), assessed indicator weights and loadings were assessed (Hair et al., 2021). Following the recommendations of Hair et al. (2021), all formative indicators with insignificant

indicator weights and loadings below .5 were deleted. Consequently, the behavioral (weight: .093, loading: .381) and cognitive (weight: -.297, loading: -.269) dimensions of inertia, dissatisfaction (weight: .075, loading: .415), distrust (weight: -.303, loading: .251), habit (weight: -.071, loading: .236), and perceived risk (weight: .022, loading: .145) were excluded from further analysis, due to their insufficient relative and absolute contributions to their respective higher-order construct (Hair et al., 2021). Table II [hier: Tabelle 17] shows the formative indicator weights and loadings.

4.3.5.3 Structural model assessment

Before evaluating the structural model, variance inflation factors (VIF) were calculated for all predictor constructs. Since no VIF values exceeded 3, multicollinearity was not considered an issue in this study (Hair et al., 2021). To assess the structural model, a bootstrapping analysis with 10,000 resamples was conducted. The results (see Table III [hier: Tabelle 18]) show that the push factor has no significant effect on switching intention ($\beta=.038$, confidence interval_{95%} [-.070, .143], H₁). In contrast, the pull factor significantly increases switching intention ($\beta=.633$, confidence interval_{95%} [.542, .724], H₂), and the mooring factor significantly decreases switching intention ($\beta=-.232$, confidence interval_{95%} [-.352, -.106], H₃). The mooring factor does not moderate the relationship between the push factor and switching intention ($\beta=.018$, confidence interval_{95%} [-.064, .093], H₄). However, it moderates the relationship between the pull factor and switching intention ($\beta=-.115$, confidence interval_{95%} [-.183, -.045], H₅), indicating that the stronger the mooring factor, the weaker the relationship between the pull factor and switching intention. Finally, switching intention significantly increases switching behavior ($\beta=.228$, confidence interval_{95%} [.085, .344], H₆), and the mooring factor moderates the relationship between switching intention and switching behavior ($\beta=-.162$, confidence interval_{95%} [-.276, -.034], H₇), indicating that the stronger the mooring factor, the weaker the relationship between switching intention and switching behavior. Regarding control variables, both age and gender show no significant effects. In terms of in-sample-predictive power, the model explains 58.3% of the variance in switching intention and 9.0% of the variance in switching behavior. To assess the out-of-sample predictive power of the model, PLSpredict was applied (Shmueli et al., 2016) using 10-fold cross-validation with 10 repetitions, following the approach recommended by Hair et al. (2021). Since the model includes higher-order constructs, the analysis was conducted on the construct scores rather than the raw data. The results show that PLS-SEM yields lower root mean squared error (RMSE) and mean absolute error (MAE) values than the linear model (LM) for both switching intention (RMSE:

PLS=.662, LM=.679; MAE: PLS=.509, LM=.517) and switching behavior (RMSE: PLS=.978, LM=.980; MAE: PLS=.433, LM=.443), indicating high predictive power.

4.3.5.4 Common method bias

The design of this study minimizes the likelihood of common method bias (CMB) occurring *ex ante* by incorporating a temporal separation throughout the data collection process (i.e., two-wave survey) (Podsakoff et al., 2012; Viswanathan and Kayande, 2012). To assess the potential risk of CMB *ex post*, the marker variable technique was employed (Lindell and Whitney, 2001) using the attitude towards blue marker variable (Miller and Simmering, 2023). The results indicated no statistical evidence for CMB.

4.3.5.5 Additional considerations

In their recommendations for the appropriate use of PLS-SEM, Evermann and Rönkkö (2023a) suggest including the Composite Equivalence Index (CEI) as a basic diagnostic. The CEI is calculated by correlating the construct scores from the PLS-SEM analysis with unweighted composites (Rönkkö et al., 2022). The individual CEI values for the latent constructs in the structural model were .998 for the push factor, .919 for the pull factor, .926 for the mooring factor, and .999 for switching intention. According to Rönkkö et al. (2022), a minimum CEI value below the threshold of .95 is necessary to justify the use of PLS-SEM over simple regression using unweighted sums. This condition is met in the model, with the lowest CEI value being .919.

Evermann and Rönkkö (2023a) also recommend assessing statistical power using the simulation-based approach proposed by Aguirre-Urreta and Rönkkö (2015). However, this method could not be applied using the *matrixpls* package (version 1.0.15) in R due to the presence of formative higher-order constructs in the model. Instead, G*Power (Faul et al., 2007) was used to conduct a regression-based power analysis based on the construct scores exported from the PLS-SEM analysis. The results indicate high achieved power for both switching intention (Number of predictors: 5, R^2 : .583, Significance level: .05, Sample size: 225, Power: >.999) and switching behavior (Number of predictors: 2, R^2 : .09, Significance level: .05, Sample size: 225, Power: .992).

Variable	CA	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. DIS	.895	.754	.868																
2. PET	.964	.904	.171	.951															
3. DTR	.806	.799	.621	.071	.894														
4. BSQ	.844	.752	.624	.160	.746	.867													
5. AAT	.878	.668	.127	.353	.050	.227	.817												
6. PUS	.970	.892	.148	.123	.237	.455	.404	.945											
7. SNO	.954	.956	.157	.274	.208	.322	.499	.351	.978										
8. PEB	.892	.755	.064	.525	-.010	.090	.475	.283	.291	.869									
9. SCO	.926	.817	-.039	-.126	.113	.112	-.232	.106	-.036	-.123	.904								
10. HAB	.862	.876	-.446	-.155	-.473	-.461	.046	-.178	-.164	-.020	-.100	.936							
11. ABI	.878	.891	-.510	-.331	-.496	-.472	-.313	-.156	-.365	-.134	.176	.458	.944						
12. BBI	.954	.915	-.209	-.214	-.155	-.166	-.031	.017	-.170	-.071	.104	.412	.424	.957					
13. CBI	.922	.843	.079	.068	.181	.256	.271	.243	.137	.180	.161	.084	.009	.287	.918				
14. LCS	.976	.891	-.224	-.389	-.218	-.297	-.512	-.377	-.461	-.410	.099	.180	.386	.205	-.182	.944			
15. PRI	.752	.767	-.024	-.056	-.061	-.026	-.139	.005	-.037	-.052	.235	.019	.112	.014	-.040	.050	.876		
16. SWI	.902	.836	.167	.349	.110	.257	.695	.462	.473	.372	-.216	-.125	-.414	-.165	.117	-.473	-.083	.914	
17. SWB	-	-	.180	.150	.139	.176	.189	.105	.143	.086	-.115	-.200	-.203	-.112	-.008	-.098	-.089	.222	-

Tabelle 16: Cronbach's Alpha, AVE, and Fornell-Larcker Criterion

Note. The diagonal elements (in bold) represent the square roots of the AVE. CA: Cronbach's Alpha, AVE: Average Variance Extracted, DIS: Dissatisfaction, PET: Perceived Environmental Threats, DTR: Distrust, BSQ: Bad Service Quality, AAT: Alternative Attractiveness, PUS: Perceived Usefulness, SNO: Subjective Norm, PEB: Perceived Environmental Benefits, SCO: Switching Costs, HAB: Habit, ABI: Affective-Based Inertia, BBI: Behavioral-Based Inertia, CBI: Cognitive-Based Inertia, LCS: Low Consciousness for Sustainable Consumption, PRI: Perceived Risk, SWI: Switching Intention, SWB: Switching Behavior

Second-Order Construct	First-Order Construct	Indicator Weight	t value	Indicator Loading	t value
Inertia	Affective-Based Inertia	.884	7.977	.929	12.220
	Behavioral-Based Inertia	.093	.455	.381	2.495
	Cognitive-Based Inertia	-.297	-1.542	-.269	-1.267
Push	Dissatisfaction	.075	.152	.415	2.820
	Perceived Environmental Threats	.712	7.234	.802	9.791
	Distrust	-.303	-1.314	.251	1.204
	Bad Service Quality	.655	3.451	.607	5.488
Pull	Alternative Attractiveness	.735	9.025	.943	39.970
	Perceived Usefulness	.261	3.396	.628	8.641
	Subjective Norm	.175	2.150	.641	9.432
	Perceived Environmental Benefits	.032	.409	.507	6.834
Mooring	Switching Costs	.227	2.109	.389	3.466
	Habit	-.071	-.781	.236	1.842
	Inertia	.472	4.172	.730	9.897
	Low Consciousness for Sustainable Consumption	.639	7.636	.835	16.300
	Perceived Risk	.022	.095	.145	.917

Tabelle 17: Formative Indicator Weights and Loadings

Hypothesis	Path	β	S.E.	t value	2.5% CI	97.5% CI	Result
H ₁	Push → Switching Intention	.038	.055	.669	-.070	.143	Rejected
H ₂	Pull → Switching Intention	.633	.046	13.583	.542	.724	Supported
H ₃	Mooring → Switching Intention	-.232	.063	-3.673	-.352	-.106	Supported
H ₄	Push × Mooring → Switching Intention	.018	.040	.607	-.064	.093	Rejected
H ₅	Pull × Mooring → Switching Intention	-.115	.035	-3.438	-.183	-.045	Supported
H ₆	Switching Intention → Switching Behavior	.228	.066	3.518	.085	.344	Supported
H ₇	Switching Intention × Mooring → Switching Behavior	-.162	.061	-2.733	-.276	-.034	Supported
-	Age → Switching Behavior	-.009	.052	-.144	-.112	.090	-
-	Gender → Switching Behavior	.030	.064	.458	-.104	.146	-

Tabelle 18: PLS-SEM Results

Note. $R^2_{\text{Switching Intention}}$: 58.3%, $R^2_{\text{Switching Behavior}}$: 9.0%, β : Bootstrapped Path Coefficient, S.E.: Standard Error, CI: Confidence Interval

4.3.6 Discussion

By applying the PPM model to study the factors that influence switching towards environmentally sustainable service providers, this research provides valuable contributions relevant to both researchers and practitioners.

4.3.6.1 Theoretical contribution

First, considering prior service switching research (e.g., Matt et al., 2015; Ye and Potter, 2011), it is unexpected that the push factor does not significantly increase switching intention. Even the addition of a relatively new context-specific push variable, perceived environmental threats (Wang et al., 2020), does not change this result. Notably, however, perceived environmental threats has the strongest relative influence on the push factor within the formative measurement model (see Table II [hier: Tabelle 17]). This suggests that perceived environmental threats associated with the status quo could become a key variable in future PPM model studies within sustainability contexts. As a whole, this underscores the importance of context-specific variables in the application of the PPM model. When considering the reasons for the insignificant effect of the push factor, it is important to recognize that the structural model evaluates the influence of predictors relative to one another. As shown in Table I [hier: Tabelle 16], the push variables correlate positively with switching intention, consistent with expectations. However, the relative influence of the push factor diminishes when compared to the stronger effects of the pull factor and the mooring factor. A potential explanation for this is that users do not experience a strong motivation to defect from their incumbent search engine (e.g., Google), but rather become motivated by the appeal of a more sustainable option. Thus, switching in this context is not about escaping a negative origin but about pursuing a better alternative—making the push factor less relevant.

Second, the pull factor exerts the strongest relative influence on switching intention. This result is consistent with previous findings in services marketing (e.g., Bansal et al., 2005) and meta-analytical findings on the PPM model (Marx, 2025). Unexpectedly, compared to its counterpart, perceived environmental threats of the status quo, perceived environmental benefits of the alternative did not exhibit a significant relative influence on the pull factor within the formative measurement model (see Table II [hier: Tabelle 17]). Instead, alternative attractiveness, perceived usefulness, and subjective norm emerged as having a significant relative influence on the pull factor. One potential explanation could be that while users value environmental benefits (see Table

I [hier: Tabelle 16]), they do not carry enough relative weight to drive switching intention, unless coupled with more personally relevant motivators such as perceived usefulness, attractiveness, or social pressure.

Third, in line with the proposed hypothesis and prior literature (e.g., Bansal et al., 2005; Matt et al., 2015; Ye and Potter, 2011), the mooring factor significantly decreases switching intention. The results reveal that switching costs, inertia, and low consciousness for sustainable consumption exert a significant relative influence on the mooring factor, while habit and perceived risk do not (see Table II [hier: Tabelle 17]). One possible explanation is that, unlike Ye and Potter (2011), this study includes inertia and low consciousness for sustainable consumption as additional mooring variables, which exert the strongest relative influence on the mooring factor. In comparison, the relative importance of habit diminishes. Notably, this study is the first to integrate low consciousness for sustainable consumption into the PPM model. Given its strong relative influence on the mooring factor and the pivotal role of the mooring factor in explaining switching, future PPM model studies should incorporate low consciousness for sustainable consumption in sustainability-related research contexts.

Fourth, contrary to the stated hypothesis, the mooring factor does not weaken the positive relationship between the push factor and switching intention. Combined with the insignificant main effect of the push factor on switching intention, this indicates that the push factor does not increase switching intention, regardless of the level of the mooring factor. As discussed earlier, two potential reasons for the insignificant main effect are the stronger relative influence of other predictors and the fact that switching is driven more by the pursuit of a better search engine than by the rejection of the incumbent. In a context like this, where switching intention is not driven by the push factor, there is no underlying effect for the mooring factor to moderate.

Fifth, supporting the formulated hypothesis, the mooring factor weakens the positive relationship between the pull factor and switching intention. This implies that, as the level of the mooring factor increases, the influence of the pull factor on switching intention decreases. This result underlines the importance of the mooring factor: not only does it directly reduce switching intention, but it also mitigates the influence of the pull factor on switching intention.

Sixth, consistent with the stated hypothesis, switching intention increases switching behavior. This finding aligns with the broader theoretical perspective that behavioral intention serves as a reliable

predictor of actual behavior (Ajzen, 1991). Moreover, the confirmation of this hypothesis reinforces the validity of the PPM model in explaining switching behavior in general, and specifically in the context of search engines. However, despite its significant positive effect, the variance explained in switching behavior remains relatively low at 9%, considerably lower than the 23% reported by Ye and Potter (2011) in a methodologically similar PPM model study. One possible explanation is that this study is set in a sustainability context, where large intention-behavior gaps frequently occur, as revealed by previous research (Echegaray and Hansstein, 2017). Another reason may be the zero-inflated distribution of the dependent variable. The significant discrepancy between the variance explained in switching intention and switching behavior raises concerns about the relevance of studies that focus solely on intention without accounting for actual behavior. Therefore, the inclusion of behavior alongside intention is strongly encouraged in future PPM model studies.

Finally, confirming the seventh hypothesis, the mooring factor weakens the positive relationship between switching intention and switching behavior. Based on the existing body of literature, this study is the first PPM model study to examine this interaction effect, making it particularly noteworthy. This finding further underscores the critical role of the mooring factor, highlighting its threefold impact: it directly reduces switching intention, mitigates the influence of the pull factor on switching intention, and weakens the relationship between switching intention and switching behavior. Thus, the mooring factor serves as a substantial barrier, hindering users both in forming switching intentions and in translating those intentions into actions. From a theoretical perspective, these findings emphasize the importance of expanding the PPM model to include the moderating effect of the mooring factor on the relationship between switching intention and behavior.

4.3.6.2 Managerial implications

First, given the strong impact of the pull factor on switching intention, sustainable search engine providers should focus on enhancing their perceived usefulness and attractiveness relative to alternative search engines. Their marketing efforts should emphasize their environmental benefits, such as real-zero emissions and contribution to global reforestation projects, alongside user-friendly features and competitive search performance. Additionally, sustainable search engine providers can benefit from subjective norm, as users may feel encouraged to switch when they perceive that important others support environmentally sustainable alternatives. For example,

collaborations with influential public figures, such as influencers on social media platforms, can create perceived social pressure, encouraging users to switch.

Sustainable search engine providers, such as Ecosia, are already actively working to address pull factors in their marketing efforts. However, given the findings of this research on the threefold impact of mooring factors, there is a need for providers to improve in managing these barriers to switching. Lowering switching costs is essential. Sustainable search engine providers could develop tools that allow users to seamlessly transfer bookmarks, preferences, and search histories from incumbent search engines, minimizing procedural challenges and creating a smoother transition process. Moreover, addressing inertia is a critical step. Gamification elements, which have generally been found to be effective marketing measures (Barari, 2024), such as tracking a user's individual contribution to reforestation projects, can help to disrupt entrenched usage patterns and motivate switching. Features like leaderboards showcasing top contributors or achievement badges for initial milestones, such as making the first few searches and thereby planting the first tree, could create a sense of accomplishment and social recognition that encourages adoption. Furthermore, an onboarding tutorial presented when users first access the website or download the app could further reduce reluctance about switching. Lastly, it is crucial for sustainable search engines to address low consciousness for sustainable consumption through educational campaigns that raise awareness about the environmental impact of unsustainable consumption. Collaborations with educational institutions can amplify these efforts, fostering informed decision-making and encouraging users to adopt sustainable alternatives.

In addition to provider-level strategies, the findings of this study have important implications for policymakers and regulatory institutions aiming to foster environmental sustainability. More recently, the United Nations has highlighted the growing environmental costs associated with the expansion of digital infrastructure—including increased electricity and water consumption, greenhouse gas emissions, and electronic waste (United Nations, 2025). One way to mitigate these environmental impacts is to promote user switching toward more sustainable alternatives. This study finds that, in the context of search engines, switching behavior is not primarily driven by the push factor, but rather by the pull factor and the mooring factor. This pattern likely emerges because incumbent systems are perceived as functional and non-problematic, reducing the motivation to defect. Instead, users are driven by the appeal of more sustainable options. It is proposed that this

insight is transferable to other service domains where sustainable alternatives compete with dominant incumbents (e.g., green finance, eco-tourism, mobility services).

In line with this reasoning, policy interventions may be more effective when they emphasize the positive attributes of sustainable alternatives rather than focusing solely on the negative aspects of conventional systems. For example, communication strategies that highlight benefits such as reduced carbon emissions, improved air quality, and support for global reforestation may resonate more strongly with users than those that stress the harms of current practices. At the same time, the findings of this study underline the importance of addressing the mooring factor, which consists of personal elements that anchor users to their current search engine. Policy messages, therefore, should not only stress the advantages of sustainable options but also address mooring variables such as habit, inertia, or switching costs.

4.3.6.3 Limitations and further research

The results and implications of this study should be considered in light of some important limitations. First, from a methodological perspective, this study is based on a German convenience sample recruited through Clickworker. Future research could build on these findings by replicating the study using representative samples from specific populations. Furthermore, cross-cultural comparisons would provide valuable insights, given that environmentally sustainable behavior has been shown to vary depending on cultural values (e.g. Nguyen et al., 2017).

Second, although this study employed a multi-wave survey design to assess actual switching behavior, switching intention and the independent variables were measured shortly after a brief introduction to Ecosia. As many participants were previously unfamiliar with this search engine, their responses may be based on hypothetical rather than experience-based evaluations. This raises concerns about potential method bias (MacKenzie and Podsakoff, 2012). Future research could address this issue by incorporating study designs that ensure participants interact with the alternative system before measurement.

Third, this study measured switching behavior based on respondents' self-reported usage. Inaccuracies in how respondents estimate their usage may introduce measurement error. Incorporating objective data sources, such as actual time spent using a specific search engine obtained through browser logs, would provide a valuable validation. In addition, future research

could adopt a mixed-methods approach—for example, by conducting follow-up interviews—to gain deeper insights into users’ switching behavior.

Fourth, the measure of switching behavior in this study is zero-inflated, with many participants (84.4%) showing no change in their Ecosia usage percentage, while others exhibited positive (10.67%) or negative changes (4.89%). Although PLS-SEM is a non-parametric method and well-suited for analyzing metric variables (Hair et al., 2021), hurdle models (e.g., Cragg, 1971) might offer a more suitable approach for zero-inflated data. However, given the large proportion of zeroes and the small overall number of non-zero observations in this study, applying a hurdle model is not feasible (Cragg, 1971). Nevertheless, when applicable, this approach should be considered in future research.

Fifth, the second survey was conducted two months after the initial survey to assess switching behavior. While this timeframe aligns with recommendations from prior research (e.g., Bansal et al., 2005; Marx, 2025), the two-month period is somewhat arbitrary. For example, participants may have switched to Ecosia during this period but subsequently stopped using it, or they may have needed more time to adopt it. Future research could investigate varying timeframes and, ideally, implement a longitudinal study design that collects data at more frequent intervals, such as weekly, to gain a more comprehensive understanding of the dynamics of switching over time.

Finally, this study specifically focused on Ecosia as an environmentally sustainable search engine. While Ecosia serves as a good example, it does not represent environmentally sustainable services as a whole. Thus, further research should examine other categories of sustainable services to increase external validity.

4.4 Beitrag 4: From conversational agents back to human agents? A two-wave study of the drivers and inhibitors of customer switching behavior

Autoren	Tobias Marx, Marco Hubert
Zitation	-
URL	-
Keywords	Conversational agents, Chatbots, Artificial intelligence, Human agents, Customer service, Switching behavior, Push-pull-mooring model
Status	In Begutachtung

Tabelle 19: Kurzübersicht zu Beitrag 4

Quelle: Eigene Darstellung

4.4.1 Abstract

Purpose: The rise of artificial intelligence (AI) has reignited a central debate about the future of work: Will machines replace humans? In customer service, companies increasingly replace human agents (HAs) with AI-powered conversational agents (CAs) because they provide efficiency gains, instant responses, and constant availability. Yet customer service cannot currently operate without HAs, as customers continue to seek their assistance for different reasons. Against this background, this study examines which factors determine switching from CAs to HAs in customer service.

Method: A two-wave online survey of German customers captures both switching intention and switching behavior over a two-month period. The research model is based on the push-pull-mooring model. The data is analyzed with structural equation modeling.

Results: The pull factor, primarily driven by perceived usefulness of HAs, increases switching intention. The mooring factor, driven mainly by inertia, inhibits switching intention. Surprisingly, the push factor, primarily driven by dissatisfaction and perceived inefficiency of CAs, reduces switching intention, suggesting disengagement from customer service altogether rather than substitution. Task difficulty emerges as a central antecedent, intensifying push and pull factors while weakening the mooring factor. Switching intention increases switching behavior.

Conclusion: This study finds that the current advantage of HAs lies in their ability to resolve complex service tasks. CAs still struggle with difficult requests. Over time, however, as CAs become capable of handling all customer demands, this advantage may erode. Thus, the continuing role of HAs in customer service may only be a temporary consequence of current technological limitations.

4.4.2 Introduction

The rise of artificial intelligence (AI) has reignited a central debate about the future of work: Will machines replace humans (United Nations, 2025)? In customer service, this question is especially pressing: OpenAI's CEO Sam Altman recently predicted that many customer service roles currently performed by human agents (HAs) over phone or computer "will be better done by an AI," accelerating job losses in the sector (Spirlet, 2025). Salesforce has already taken this step, cutting 4,000 customer support jobs and replacing them with AI agents (Sorace, 2025). Such developments reflect the belief that AI-powered conversational agents (CAs) can transform customer service by providing instant responses, ensuring 24/7 availability (Thomaz et al., 2020; Gelbrich et al., 2021), and reducing operational costs for businesses (Sands et al., 2020). Consequently, companies across various industries have integrated CAs into their customer support systems (Li and Zhang, 2023), handling high volumes of inquiries efficiently (De Andrade et al., 2022).

However, despite their potential, CAs often struggle with complex queries, unexpected scenarios, and the absence of human emotions, leading to user frustration that can result in service breakdowns or prompt customers to seek assistance from HAs instead (Lu et al., 2024). While prior research has extensively examined CA acceptance and use (e.g., Blut et al., 2024; Hubert et al., 2025; Li and Zhang, 2023), customer switching behavior from CAs to HAs remains underexplored (Lu et al., 2024). This switching direction is particularly important because it undermines the efficiency gains of automation through CAs and signals potential weaknesses in CA service design. For companies, an important challenge lies in determining whether such switching should be minimized to preserve cost reductions or facilitated as a safeguard to ensure problem resolution. Since CA failures are currently inevitable to some extent (Lv et al., 2022), it is crucial for companies to understand the drivers and inhibitors of customer switching behavior toward HAs.

Therefore, this study answers the following research question: What factors determine customers' switching intention and behavior from CAs to HAs?

To address this question, this study applies the PPM model, an established framework in the literature for explaining service switching intention and behavior (Bansal et al., 2005). Building on the PPM model, the study contributes by examining the underexplored switching direction from CAs to HAs, employing a longitudinal two-wave design that captures both intention and subsequent behavior, extending the model with context-specific variables, identifying task difficulty as a key antecedent and adding cultural breadth through a German consumer sample.

The rest of this paper is structured as follows: Chapter 2 reviews the conceptual and theoretical background. Chapter 3 describes the methodological approach. Chapter 4 presents the results. Chapter 5 discusses the findings with a focus on their theoretical and practical implications as well as the study's limitations and avenues for future research. Finally, Chapter 6 concludes the paper.

4.4.3 Conceptual and theoretical background

4.4.3.1 Conversational agent-human agent switching

A CA (also referred to as a chatbot) in customer support is an AI-driven program designed to interact with customers through natural language (Kim & Hur, 2023; Rese & Tränkner, 2024). In contrast, a HA is a customer service employee who provides support through direct interpersonal interaction. Switching from a CA to a HA refers to a customer's decision to discontinue an interaction with the CA and instead seek assistance from a HA. In many service settings, companies encourage customers to engage with a CA first, while still allowing them to switch to a HA when needed (Lu et al., 2024). To gain an overview of the current state of research and to identify existing gaps, we conducted a focused literature review on CA-HA switching. For this purpose, we searched the Scopus database using the query: TITLE-ABS-KEY ("conversational agent") OR TITLE-ABS-KEY ("chatbot") AND TITLE-ABS-KEY ("human") AND TITLE-ABS-KEY ("switching"). This search yielded 31 potentially relevant papers. After screening them for relevance, we identified 5 studies that specifically address CA-HA switching in customer service. An overview of these studies is presented in Table I [hier: Tabelle 20].

Authors (Year)	Title	Switching direction	Theoretical background	Data type	Sample population	Method	Dependent variable	N	R ²
Cheng et al. (2022)	Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms	CA → HA	Stimulus-organism-response framework	Cross-sectional	China	PLS-SEM	Switching intention	302	SI: .206
Li and Zhang (2023)	Chatbots or me? Consumers' switching between human agents and conversational agents	HA → CA	Push-pull-mooring model	Cross-sectional	Taiwan	PLS-SEM	Switching intention*	441	SI: .40
Lu et al. (2024)	The effect of the anthropomorphic design of chatbots on customer switching intention when the chatbot service fails: An expectation perspective	CA → HA	Anthropomorphic design and service recovery expectations	Cross-sectional	China	PLS-SEM	Switching intention	404, 338	SI: .505 SI: .677
Chen et al. (2025)	Exploring the varying effects of chatbot service quality dimensions on customer intentions to switch service agents	HA → CA	Stimulus-organism-response framework	Cross-sectional	China	PLS-SEM	Switching intention	575	NA
Huang (2026)	Asking fintech voice Chatbots: Explaining consumer switching intention by status quo bias theory	HA → CA	Status quo bias theory	Longitudinal (Three survey waves)	Taiwan	LGCM	Switching intention	330	NA
This study	Switching from Conversational Agents to Human Agents: An Empirical Study from the Perspective of the Push-Pull-Mooring Model	CA → HA	Push-pull-mooring model	Longitudinal (Two survey waves)	Germany	PLS-SEM	Switching intention, Switching behavior	240	SI: .365, SB: .065

Tabelle 20: Literature comparison of empirical studies on CA-HA switching in customer service

Note. CA: Conversational agent, HA: Human agent, PLS-SEM: Partial least squares structural equation modeling, LGCM: Latent growth curve model, SI: Switching Intention, SB: Switching Behavior, *The measure is labeled as switching behavior, but the indicators reflect switching intention rather than switching behavior, which can only be observed at a point later than the measure of intention.

As Table I [hier: Tabelle 20] highlights, prior studies differ in terms of switching direction, theoretical background, data type, sample population, method, and dependent variable. Building on these insights, this study advances research on switching between CAs and HAs in several ways. First, it examines CA to HA switching using a longitudinal two-wave design, whereas prior CA to HA switching work is cross-sectional (i.e., Cheng et al., 2022; Lu et al., 2024) and the only other longitudinal study investigates the opposite switching direction (i.e., Huang, 2026). Second, beyond intention, it is the only study that captures subsequent self-reported switching behavior, offering behavioral validation in this domain. Third, it applies and extends the PPM model to the CA to HA switching context, complementing PPM evidence from HA to CA switching (Li & Zhang, 2023). Fourth, it goes beyond the modeling of switching intention by also explaining variance in the underlying push, pull, and mooring factors. In doing so, it identifies task difficulty as a key driver, explaining up to 71% of variance. Including task difficulty is particularly relevant in the CA-HA switching context because customer service requests can vary greatly in complexity. While CAs can handle simple and routine inquiries effectively, they often fail when interactions become more demanding (Lu et al., 2024). Finally, by drawing on a German consumer sample, the study adds cultural breadth to a literature base otherwise concentrated in China and Taiwan, thereby strengthening cross-cultural generalizability.

4.4.3.2 Push-pull-mooring-model

Originally developed in migration research (Ravenstein, 1885; Lee, 1966; Bogue, 1969; Moon, 1995), the push-pull-mooring (PPM) model offers a robust theoretical framework for explaining why individuals relocate from one place to another. It comprises three core components: the push factor, which drives individuals away from their current location (Stimson & Minnery, 1998); the pull factor, which attracts them toward an alternative destination (Moon, 1995); and the mooring factor, which encompasses personal and social elements that may either constrain individuals in their current location or facilitate their movement elsewhere (Moon, 1995). Individuals typically evaluate the push and pull factor in a direct comparison with one another, whereas the mooring factor is considered separately, providing the context in which this comparison takes place (Lee, 1966). Therefore, the mooring factor is understood to moderate the influence of the push and pull factors on the migration decision (Lee, 1966).

Bansal et al. (2005) pioneered the application of the PPM model in service research, showing its strong predictive power for service switching intentions and behaviors, thereby stimulating subsequent research. Since then, the model has been adapted across various other contexts (Marx, 2025). In the human-computer interaction domain, recent applications of the PPM model are, for example, studies on users' switching between mobile personal cloud storage services (Cheng et al., 2019), consumers' adoption of augmented reality beauty applications (Nugroho & Wang, 2023), and customers' transition from traditional to AI-based banking services (Lian & Li, 2025).

4.4.3.3 Hypotheses development

4.4.3.3.1 Push factor

The push factor motivates customers to switch from CAs to HAs. Building on prior research, the push factor is captured through dissatisfaction, bad service quality, distrust, perceived inefficiency, and negative attitude.

Dissatisfaction refers to a psychological state that arises when customers' actual service experiences fall short of their prior expectations (Oliver, 1981). Whereas satisfaction typically fosters continued usage intentions (Bhattacharjee, 2001), dissatisfaction undermines them. In the context of this study, dissatisfied users should be less inclined to persist with CA-based interactions and more likely to seek assistance from a HA instead. Empirical evidence for the positive relationship between dissatisfaction and switching intention is, for example, provided by Ye and Potter (2011).

Bad service quality can be understood as customers' overall judgment of the inferiority of a CA-based service encounter (Bitner & Hubbert, 1994). Negative assessments of service quality have been shown to drive unfavorable behavioral responses, including a greater likelihood of switching to alternatives (Zeithaml et al., 1996). Perceptions of inadequate CA service quality should prompt users to discontinue the interaction with the CA and seek assistance from a HA instead. Empirical evidence supporting a positive relationship between bad service quality and switching intention is provided, for example, by Matt et al. (2015).

Distrust can be understood as the customer's belief that the CA is unreliable and cannot be depended upon to resolve service issues effectively (Sirdeshmukh et al., 2002). While trust generally encourages favorable behavioral intentions such as continued use (Kim et al., 2013), distrust diminishes them. Customers who distrust a CA should therefore be more inclined to

abandon the interaction and turn to a HA, who they perceive as more dependable. Empirical support for the positive link between distrust and switching intention is provided, for example, by Matt et al. (2015).

Perceived inefficiency can be defined as the customer's perception that interacting with a CA takes more time to reach the desired outcome compared to a HA (Zhu et al., 2023). Perceived inefficiency should positively influence switching intention toward a HA because users expect customer service to provide quick solutions (Canhoto & Clark, 2013; Parasuraman et al., 1988). When a CA is seen as taking too much time and not delivering the desired outcome, users are motivated to switch to a HA, who they perceive as more capable of resolving the issue. Empirical evidence of the positive effect of perceived inefficiency on switching intention is provided, for example, by Chen et al. (2024) and Zhu et al. (2023).

Negative attitude toward the CA can be defined as a learned predisposition to respond in a consistently unfavorable manner toward the CA (Ajzen, 1991; MacKenzie & Lutz, 1989). Following Ajzen and Fishbein (1980), such attitudes are shaped by beliefs about CA attributes (e.g., the ability to understand user queries) and their evaluation. A negative attitude toward the CA should increase switching intention because unfavorable evaluations of its attributes reduce users' willingness to continue the interaction, leading them to seek support from a HA instead. Empirical evidence for the strong relationship between attitude and intention is plentiful in general (e.g., Ajzen, 1991), and there is also support in the specific context of CAs (de Cosmo et al., 2021). Overall, we hypothesize:

H₁: The push factor, operationalized by dissatisfaction, bad service quality, distrust, perceived inefficiency, and negative attitude toward the CA, positively influences switching intention.

4.4.3.3.2 Pull factor

The pull factor attracts customers to switch from CAs to HAs. Based on prior research, the pull factor is captured through alternative attractiveness, perceived usefulness, subjective norm, perceived empathy, and perceived adaptability.

Alternative attractiveness refers to customers' perceptions regarding the positive characteristics of the HA compared to the CA (Bansal et al., 2005; Jones et al., 2000; Ping, 1993). In the context of CA-HA switching, alternative attractiveness should positively influence switching intention because perceiving the HA as an attractive alternative increases the perceived benefits of choosing

the HA over the CA (Jones et al., 2000). Empirical support for a positive link between alternative attractiveness and switching intention has been shown, for example, by Chang et al. (2014).

Perceived usefulness refers to the extent to which a customer believes that interacting with a HA enhances the effectiveness of resolving their service issue (Davis, 1989). Perceived usefulness should increase switching intention because when the HA is seen as more useful than the CA, the perceived benefits of switching rise. Empirical evidence for this relationship has, for example, been provided by Lenz et al. (2023).

Subjective norm refers to the perceived social pressure to switch from a CA to a HA based on the opinions of important others (Ajzen, 1991). Important others may disapprove of CAs for various reasons, such as the perception that they generally deliver a worse customer experience than HAs (Ashfaq et al., 2020), which can increase customers' intention to switch to a HA in order to meet these social expectations. Empirical evidence for a positive relationship between subjective norm and switching intention is provided, for instance, by Sun et al. (2017).

Perceived empathy can be defined as the extent to which the HA is seen as providing caring and individualized attention to the customer (Parasuraman et al., 1988). High perceived HA empathy should encourage users to switch from the CA to a HA because they desire the caring and individualized attention that only a human can provide. Regarding empirical evidence, Umasuthan et al. (2017) show that employees' empathy can drive behavioral intentions such as revisiting and recommendation intentions in the hotel context. Moreover, in the context of CA-HA switching, Li and Zhang (2023) find that low empathy displayed by HAs is positively associated with switching intention.

Perceived adaptability refers to the extent to which a HA is seen as able to adjust their behavior to the individual demands of the customer service interaction (Hartline & Ferrell, 1996). High HA adaptability may increase switching intention from the CA to a HA because users prefer interactions tailored to their individual needs (Gwinner et al., 2005), and HAs are generally more flexible than CAs in adjusting to such demands (Ashfaq et al., 2020). Regarding empirical evidence in the context of CA-HA switching, Li and Zhang (2023) find that low adaptability displayed by HAs is positively correlated with switching intention. Overall, we hypothesize:

H₂: The pull factor, operationalized by alternative attractiveness, perceived usefulness, subjective norm, perceived empathy, and perceived adaptability, positively influences switching intention.

4.4.3.3.3 Mooring factor

The mooring factor anchors customers to CAs. Building on prior research, the mooring factor is captured through switching costs, inertia, habit, perceived risk, social interaction anxiety, and technological affinity.

Switching costs refer to customers' anticipated costs associated with switching from a CA to a HA (Burnham et al., 2003; Jones et al., 2002). Switching costs should decrease switching intention because they act as obstacles that make users less willing to change their mode of interaction (Jones et al., 2000; 2002). Empirical evidence for the negative relationship between switching costs and switching intention is provided, for instance, by Chang et al. (2014).

Inertia refers to customers' attachment to, and persistence in, interacting with the CA, even when a HA may represent a better alternative (Polites & Karahanna, 2012). Inertia is conceptualized as a first-order reflective, second-order formative multidimensional construct consisting of an affective, a behavioral, and a cognitive dimension (Polites & Karahanna, 2012). Inertia should decrease switching intention because it leads customers to perceive the relative benefits of the HA as lower than those of the CA. Empirical evidence for the negative relationship between inertia and switching intention is provided, for example, by Sun et al. (2017).

Habit can be understood as a learned response that is activated automatically in response to environmental cues (Polites & Karahanna, 2013). Habitual behavior can be advantageous, as it demands less cognitive effort than conscious decision-making, is associated with lower stress, and helps prevent feelings of being overwhelmed (Polites & Karahanna, 2012). In the context of customer service, many customers are accustomed to dealing with CAs, as these are often the first option presented when seeking support (Lu et al., 2024). As a result, they may be less inclined to carefully evaluate the advantages of switching to a HA. Empirical evidence for the negative relationship between habit and switching intention is provided, for instance, by Cheng et al. (2019).

Perceived risk refers to customers' uncertainty about the reliability of the performance of a HA in customer service (Sun, 2014; Sweeney et al., 1999). Perceived risk should decrease switching intention from CAs to HAs, as doubts about the reliability of a HA's performance can make staying with the CA feel like the safer option. Empirical evidence for the negative relationship between perceived risk and switching intention is provided, for example, by Chen et al. (2023).

Social interaction anxiety refers to the distress customers may feel when interacting with a HA, such as fears of saying the wrong thing or not knowing how to respond (Mattick & Clarke, 1998). Social interaction anxiety should decrease switching intention because customers who feel uncomfortable in direct interpersonal exchanges are likely to avoid human contact and instead continue using the CA, which feels less socially demanding. There is no empirical evidence for the relationship between social interaction anxiety and switching intention, as this study is the first to examine it. However, previous findings show that social anxiety can increase problematic use of CAs (Hu et al., 2023).

Technological affinity refers to the extent to which individuals tend to actively approach interaction with new technical systems (Franke et al., 2019). High technological affinity should reduce switching intention to HAs because users who are comfortable engaging with technical systems are more likely to persist with CAs rather than seeking human support. Empirical evidence supporting this argument is provided, for example, by Sham et al. (2023), who showed that higher technology affinity increases switching intention from traditional grocery delivery services to drone delivery services. Overall, we hypothesize:

H₃: The mooring factor, operationalized by switching costs, inertia, habit, perceived risk, social interaction anxiety, and technological affinity, positively influences switching intention.

Migration research highlights that the mooring factor can influence whether push and pull factors actually lead to a migration decision (Lee, 1966). Even when push or pull pressures are strong, Lee (1966) emphasizes that individuals will only migrate if these are sufficient to outweigh the inhibiting effect of the mooring factor. Extending this idea, several PPM service switching studies have examined such moderating effects (e.g., Bansal et al., 2005; Hsieh et al., 2012; Ye & Potter, 2011). In the context of this study, the mooring factor may keep customers from acting on push or pull influences, thereby reducing the likelihood of switching to a HA. Thus, we hypothesize that the mooring factor weakens the positive relationship between the push factor and switching intention (**H₄**), as well as the positive relationship between the pull factor and switching intention (**H₅**).

4.4.3.3.4 Task difficulty

In this study, task difficulty refers to the extent to which customers perceive resolving their issue during a customer service interaction as challenging. The more difficult the task, the less likely the

CA is able to resolve it properly (Lu et al., 2024). If the CA fails to provide a solution, users may, for instance, become dissatisfied or perceive it as inefficient, thereby strengthening the push factor. Therefore, we hypothesize that task difficulty increases the push factor (**H₆**). At the same time, difficult tasks highlight the relative advantages of a HA, such as effective problem solving, adaptability and empathy, which enhances the pull factor. Consequently, we hypothesize that task difficulty increases the pull factor (**H₇**). Finally, higher task difficulty can weaken the mooring factor, as customers are less inclined to remain with the CA when they feel it lacks the capability to handle a challenging request. Thus, we hypothesize that task difficulty decreases the mooring factor (**H₈**).

4.4.3.3.5 Switching intention and behavior

Behavioral intentions are generally understood as self-instructions to carry out specific actions aimed at achieving a desired outcome (Sheeran & Webb, 2016) and are regarded as the strongest predictor of actual behavior (Ajzen, 1991). In this study, switching intention refers to the likelihood that customers will increasingly rely on HAs rather than CAs in customer service interactions over the next two months, while switching behavior denotes whether they actually did so in the past two months (Ajzen, 1991; Bansal et al., 2005). Meta-analytical empirical support for a strong positive link between switching intention and switching behavior is provided by Marx (2025). Therefore, we hypothesize that switching intention increases switching behavior (**H₉**). The full research model is presented in Figure 1 [hier: Abbildung 10].

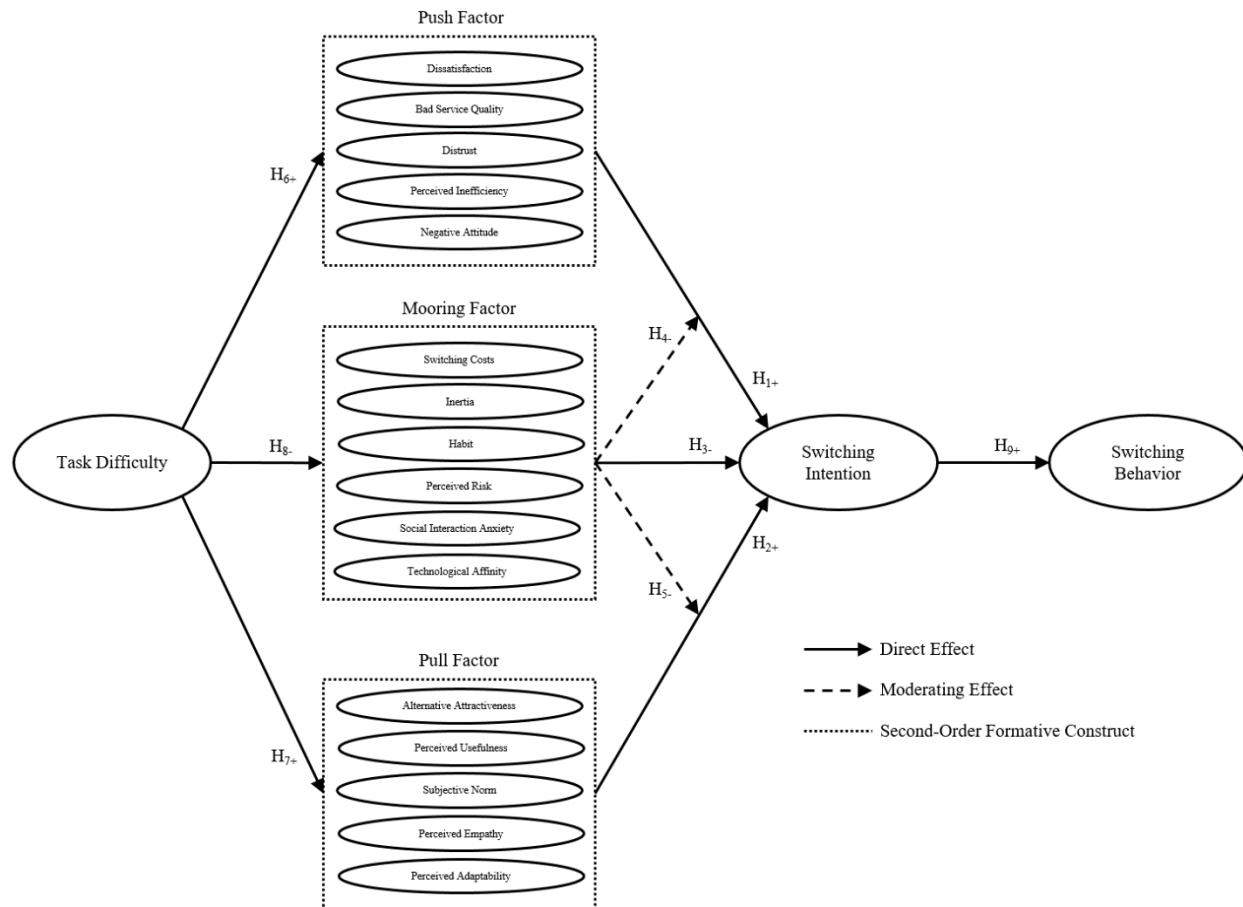


Abbildung 10: Research model

4.4.4 Method

4.4.4.1 Variable selection

A central challenge in PPM research is variable selection. A recent meta-analysis found that 148 empirical PPM studies employed 382 distinct variables to operationalize the push, pull, and mooring factors, resulting in substantial heterogeneity and limited comparability across studies (Marx, 2025). This illustrates a potential weakness of the model: its openness to a wide variety of inputs can undermine the accumulation of systematic knowledge.

At the same time, this very openness can also be considered a distinctive strength of the PPM model. It provides researchers with the flexibility to incorporate a broad range of theoretically relevant variables. By condensing these variables into higher-order constructs, this approach reduces concerns about multicollinearity, enhances model parsimony, and ensures that the underlying push, pull, and mooring factors are accurately represented (Sarstedt et al., 2019). When

guided by theory, such flexibility allows the PPM framework to integrate diverse determinants of switching while maintaining coherence with its migration-based logic (Bansal et al., 2005). Thus, variable selection in PPM research is a double-edged sword: it enables comprehensive representation of relevant influences but simultaneously raises concerns regarding the comparability of findings across studies.

Building on this consideration, the present study adopts a structured approach to variable selection. Specifically, we draw on the ten most frequently used PPM variables identified in the meta-analysis by Marx (2025) as a baseline (i.e., dissatisfaction, poor service quality, distrust, switching costs, inertia, habit, perceived risk, alternative attractiveness, perceived usefulness, and subjective norm) to ensure comparability with prior research. Beyond this baseline, we incorporate six additional predictors derived from the literature on CA-HA switching to capture context-specific influences and potentially enhance explanatory power (i.e., perceived inefficiency, negative attitude toward the CA, social interaction anxiety, technological affinity, perceived HA empathy, and perceived HA adaptability).

4.4.4.2 Conceptualization of the push, pull, and mooring factors

There are two main approaches to modeling the PPM framework: One approach treats the push, pull, and mooring variables as direct predictors of switching intention, while the other models the push, pull, and mooring factors as higher-order constructs, each composed of several lower-order variables (Marx, 2025). For example, the push factor can be modeled as a higher-order construct consisting of variables such as dissatisfaction and distrust. Within this higher-order approach, researchers have taken different paths: For example, Bansal et al. (2005) conceptualized the factors as reflective-reflective, while Ye and Potter (2011) applied a reflective-formative specification. We argue that the reflective-formative conceptualization is more appropriate and therefore adopt it in this study. For instance, as in the example above, dissatisfaction leads to being pushed away from a service provider, not the other way around; in other words, the variables cause the factor, which supports a formative specification.

4.4.4.3 Survey design

To evaluate the proposed conceptual framework, this study utilized a two-wave online survey design, with participants recruited through the crowd-working platform Clickworker. In the first survey, participants received an overview of the study's procedure, followed by a brief introduction

to CAs and HAs in customer support. A screening question assessed whether participants had interacted with a CA in customer service within the last two months. Those who had not were screened out. Using the critical incident technique, participants who qualified were then asked to recall and briefly describe a specific customer service interaction with a CA that took place in the last two months. Participants subsequently indicated the industry that best matched the described interaction, as well as their perceived task difficulty regarding the interaction. All further survey questions were answered with this recalled interaction in mind.

The survey then measured the independent variables (e.g., perceived inefficiency, perceived empathy), the dependent variable (switching intention), and sociodemographic variables. To ensure high data quality, the first survey included the attitude toward the color blue marker variable (Miller & Simmering, 2023), the gamma factor scale of socially desirable response behavior (Nießen et al., 2019), and multiple methodologically different attention checks distributed throughout the survey (Aguinis et al., 2021; Oppenheimer et al., 2009).

Two months after completing the first survey, participants were invited to complete the second survey. In this follow-up, they once again received a brief reminder introduction to CAs and HAs. They were then asked whether, in the past two months, they had used HAs more frequently than before in customer support, thereby capturing their actual, self-reported switching behavior.

4.4.4.4 Measurement

For all latent variables in our conceptual framework, we employed validated multi-item scales from prior research and adapted them to the context of this study. The measures used either seven-point agree-disagree rating scales ranging from 1 to 7 or seven-point semantic differential scales ranging from -3 to 3 (Bansal et al., 2005: Switching Behavior, Switching Intention, Alternative Attractiveness, Switching Costs; Bhattacharjee, 2001: Satisfaction; Davis, 1989: Perceived Usefulness; Limayem et al., 2007: Habit; MacKenzie & Lutz, 1989: Attitude toward CA; Miller & Simmering, 2023: Attitude toward Color Blue; Nießen et al., 2019: Social Desirability; Peters et al., 2012: Social Interaction Anxiety; Polites & Karahanna, 2012: Inertia; Sirdeshmukh et al., 2002: Trust; Sweeney et al., 1999: Perceived Risk; Taylor & Baker, 1994: Service Quality; Taylor & Todd, 1995: Subjective Norm; Wessel et al., 2019: Technology Affinity; Wilder et al., 2014: Perceived Empathy, Perceived Adaptability; Zhu et al., 2023: Perceived Inefficiency).

In preparing the data for analysis, satisfaction was reverse-coded to capture dissatisfaction, service quality to capture bad service quality, attitude toward the CA to capture a negative attitude toward the CA, and trust to capture distrust. This operationalization reflects the logic of push factors in migration research, which are defined as conditions that drive individuals away from their current location (Stimson & Minnery, 1998). Accordingly, these variables are expected to exert a positive influence on switching intention.

4.4.4.5 Pretest

To address potential comprehension difficulties and technical issues in the survey design, we first conducted a cognitive pretest with five participants who completed the questionnaire using the think-aloud method (Charters, 2003), verbalizing their thoughts as they progressed through the survey. Following this step, we implemented a quantitative pretest. Prior to analysis, we excluded respondents who failed at least one of the diverse attention checks embedded at various points in the survey (Aguinis et al., 2021; Oppenheimer et al., 2009). We also removed cases based on survey completion speed, applying a relative speed index of 2 as an upper cutoff (Leiner, 2019). In addition, respondents with extreme scores on the gamma factor scale of socially desirable responding, which is indicative of a tendency to underreport negative traits and overstate positive traits (Nießen et al., 2019), were excluded. After these quality control procedures, the final pretest sample comprised 38 participants ($M_{\text{age}} = 41.27$, $SD_{\text{age}} = 10.16$, 47.37% female). Reliability and validity of the multi-item constructs were examined through Cronbach's alpha, standardized factor loadings, and average variance extracted (AVE), all of which met established thresholds.

4.4.4.6 Main study

A total of 500 individuals were recruited via Clickworker to participate in the first survey. The same data cleaning procedures described in Chapter 3.3 were applied. In addition, we excluded respondents who, despite explicit instructions to recall a CA-based customer service interaction, reported non-customer-service-related experiences (e.g., "asked Gemini for cooking recipes"). After these steps, the sample consisted of 476 participants ($M_{\text{age}} = 40.82$, $SD_{\text{age}} = 11.66$, 42.02% female). These participants were re-contacted two months later and invited to complete the follow-up survey. In total, 240 participants ($M_{\text{age}} = 43.31$, $SD_{\text{age}} = 11.75$, 37.50% female) responded, corresponding to a response rate of 50.42%. As demographic characteristics did not differ significantly between participants who completed both surveys and those who only completed the

first, we followed Ye and Potter (2011) in concluding that non-response bias was unlikely to pose a concern.

4.4.5 Results

4.4.5.1 Preliminary considerations

In this study, partial least squares structural equation modeling (PLS-SEM) was selected over covariance-based structural equation modeling because the model contained multiple formative as well as higher-order constructs, for which PLS-SEM is regarded as the more suitable approach (Hair et al., 2021). The analyses were carried out in R (version 4.5.0) using the *sempr* package (version 2.3.4), following the guidelines provided by Hair et al. (2021). In addition, we incorporated recent recommendations on the proper application of PLS-SEM, including the emphasis on transparent reporting practices (Evermann & Rönkkö, 2023b).

4.4.5.2 Measurement model assessment

The evaluation of reflective measurement models (specified in *sempr* as mode A composites with correlation weights) in PLS-SEM begins with an examination of indicator loadings (Hair et al., 2021). Loadings above the recommended threshold of .708 indicate that a construct explains more than 50% of the variance of its indicators (Hair et al., 2021). All items met this threshold except the third and fourth indicators of switching costs, which were removed from the analysis. Next, internal consistency reliability was assessed using both composite reliability and Cronbach's alpha, with the latter preferred for its conservative estimate (Hair et al., 2021). All Cronbach's alpha values exceeded the recommended cutoff of .70, except for perceived risk, which showed a value of .66. Because this construct was measured with only two items, for which a lower threshold of .50 has been deemed acceptable (Nunnally, 1967), the construct was retained. Convergent validity was then examined using the average variance extracted (AVE). All constructs achieved AVE values above the .50 threshold (Hair et al., 2021). Finally, discriminant validity was assessed using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations (Hair et al., 2021). To satisfy the Fornell-Larcker criterion, the construct negative attitude toward the CA was removed due to a correlation of .926 with distrust. To satisfy the HTMT criterion, bad service quality was removed because of a HTMT value of .967 with distrust, and alternative attractiveness was removed because of a HTMT value of .911 with perceived usefulness. After these adjustments, the square roots of the AVE exceeded interconstruct correlations, fulfilling the Fornell-Larcker

requirement, and all HTMT values fell below the .90 threshold, confirming discriminant validity (Hair et al., 2021).

To evaluate the formative measurement model (specified in *semirn* as mode B composites with regression weights), we examined both indicator weights and loadings (Hair et al., 2021). Following Hair et al.'s (2021) guidelines, formative indicators with insignificant weights and loadings below .50 were removed. As a result, switching costs (weight = -.111, loading = -.225) and technological affinity (weight = .054, loading = .160) were excluded from further analysis, as their relative and absolute contributions to their respective higher-order constructs were insufficient. For the push factor, dissatisfaction and perceived inefficiency were the main determinants. The pull factor was driven mostly by perceived usefulness, while inertia emerged as the key determinant of the mooring factor. These constructs showed both significant weights and loadings, as displayed in Table III [hier: Tabelle 22].

As hierarchical higher-order-construct-of-higher-order-construct structures cannot be estimated in *semirn*, we analyzed the first-order reflective, second-order formative construct inertia separately before estimating the full main model. We applied the same procedure outlined above by first assessing the reflective measurement model and then the formative measurement model. In this process, the first indicator of affective inertia was removed due to a loading below .708. Moreover, when evaluating the formative measurement model, the cognitive-based inertia dimension had to be excluded because of an insignificant weight and a loading below .50 (weight = -.111, loading = -.124). After these adjustments, we saved the construct scores generated from bootstrapping analysis with 10,000 resamples and used them in the subsequent analyses.

Table II [hier: Tabelle 21] presents Cronbach's alpha, AVE, and the Fornell-Larcker criterion, and Table III [hier: Tabelle 22] shows the formative indicator weights and loadings for all retained constructs.

4.4.5.3 Common method bias

To reduce the likelihood of common method bias (CMB) in advance, the study applied a two-wave survey design that introduced temporal separation into the data collection procedure (Podsakoff et al., 2012; Viswanathan & Kayande, 2012). After data collection, we further examined the possibility of CMB by applying the marker variable technique (Lindell & Whitney, 2001), using

the attitude toward the color blue marker variable proposed by Miller and Simmering (2023). This analysis provided no statistical indication of CMB.

4.4.5.4 Structural model assessment

Before estimating the structural model, we first examined multicollinearity by calculating variance inflation factors (VIF) for all predictor constructs. None of the VIF values exceeded the threshold of 3, indicating that multicollinearity was not a concern (Hair et al., 2021). Structural relationships were then assessed using bootstrapping analysis with 10,000 resamples. The results (Table IV [hier: Tabelle 23]) reveal that the push factor has a significant negative effect on switching intention ($\beta = -.242$, confidence interval_{95%} [-.419, -.066], H₁). In contrast, the pull factor exerts a significant positive effect ($\beta = .422$, confidence interval_{95%} [.250, .583], H₂), while the mooring factor shows a significant negative effect ($\beta = -.442$, confidence interval_{95%} [-.605, -.271], H₃). No significant moderating effects were found: the mooring factor does not moderate the relationship between the push factor and switching intention ($\beta = -.047$, confidence interval_{95%} [-.211, .108], H₄), nor between the pull factor and switching intention ($\beta = .048$, confidence interval_{95%} [-.096, .196], H₅).

Task difficulty is positively related to both the push factor ($\beta = .848$, confidence interval_{95%} [.812, .880], H₆) and the pull factor ($\beta = .592$, confidence interval_{95%} [.490, .678], H₇), while it negatively affects the mooring factor ($\beta = -.520$, confidence interval_{95%} [-.622, -.399], H₈). Regarding control variables, age, gender, and industry ($N_{\text{Retail}}=77$, $N_{\text{Telecommunication}}=47$, $N_{\text{Finance}}=40$, $N_{\text{Other}}=76$) show no significant effects.

Regarding the in-sample-predictive power, the PLS-SEM model explains 36.5% of the variance in switching intention. To evaluate the out-of-sample predictive power of the model, we applied PLSpredict (Shmueli et al., 2016) with 10-fold cross-validation and 10 repetitions, as recommended by Hair et al. (2021). Because the model includes higher-order constructs, the analysis was based on the construct scores rather than the raw data. The results show that the PLS-SEM model achieves lower root mean squared error (RMSE) and mean absolute error (MAE) values than the linear model (LM) for switching intention (RMSE: PLS=.840, LM=.843; MAE: PLS=.672, LM=.674), demonstrating high predictive power.

Finally, to test H₉, we conducted a logistic regression of switching intention on switching behavior using the exported construct scores of switching intention from the PLS-SEM model. The result shows that switching intention significantly increases switching behavior ($\beta = .461$, confidence

interval_{95%} [.196, .737], H₉), supporting the hypothesis. The model explains 6.5% of the variance in switching behavior (Nagelkerke R²), with 122 participants reporting no increased reliance on HAs (coded as 0) and 118 participants reporting greater reliance (coded as 1) over the past two months.

4.4.5.5 Power analysis

Evermann and Rönkkö (2023a) recommend evaluating statistical power in PLS-SEM using the simulation-based approach introduced by Aguirre-Urreta and Rönkkö (2015). However, in our study, this approach could not be implemented because the model includes formative higher-order constructs. As an alternative, we conducted a regression-based power analysis using G*Power (Faul et al., 2007). The results indicate high achieved power for the push factor (Number of predictors: 1, R²: .717, Significance level: .05, N: 240, Power: >.999), the pull factor (Number of predictors: 1, R²: .343, Significance level: .05, N: 240, Power: >.999), the mooring factor (Number of predictors: 1, R²: .265, Significance level: .05, N: 240, Power: >.999), switching intention (Number of predictors: 8, R²: .365, Significance level: .05, N: 240, Power: >.999), and switching behavior (Odds ratio: 1.586, Prevalence of switching behavior (Y=1): .492, Significance level: .05, N: 240, Power: .928).

Variable	CA	AVE	1	2	3	4	5	6	7	8	9	10	11	12
1. DIS	.956	.884	.940											
2. DTR	.910	.788	.847	.888										
3. PIN	.845	.764	.729	.715	.874									
4. PUS	.956	.851	.612	.618	.762	.922								
5. SNO	.945	.948	.294	.334	.420	.521	.974							
6. PEM	.887	.743	.110	.109	.244	.422	.371	.862						
7. PAD	.905	.723	.197	.187	.311	.482	.413	.743	.850					
8. INE	1	1	-.665	-.679	-.629	-.564	-.294	-.168	-.210	1				
9. HAB	.925	.870	-.543	-.568	-.519	-.509	-.210	-.173	-.289	.728	.933			
10. PRI	.658	.743	-.014	-.088	-.097	-.229	-.044	-.298	-.266	.081	.181	.862		
11. SIA	.920	.711	-.222	-.167	-.206	-.172	-.079	-.180	-.140	.240	.208	.066	.843	
12. SWI	.907	.842	.295	.317	.384	.490	.359	.353	.416	-.459	-.450	-.249	-.106	.918

Tabelle 21: Cronbach's alpha, AVE, and Fornell-Larcker criterion

Note. The diagonal elements (in bold) represent the square roots of the AVE. CA: Cronbach's alpha, AVE: Average variance extracted, DIS: Dissatisfaction, DTR: Distrust, PIN: Perceived Inefficiency, PUS: Perceived Usefulness, SNO: Subjective Norm, PEM: Perceived Empathy, PAD: Perceived Adaptability, INE: Inertia, HAB: Habit, PRI: Perceived Risk, SIA: Social Interaction Anxiety, SWI: Switching Intention

Second-Order Construct	First-Order Construct	Indicator Weight	t value	Indicator Loading	t value
Push	Dissatisfaction	.564	6.309	.955	58.334
	Distrust	.128	1.529	.883	38.679
	Perceived Inefficiency	.387	5.224	.890	34.494
	Perceived Usefulness	.938	15.416	.986	91.629
Pull	Subjective Norm	.098	1.110	.581	7.923
	Perceived Empathy	-.100	.112	.395	4.301
	Perceived Adaptability	.082	.123	.502	5.736
	Inertia	.811	7.697	.969	48.349
Mooring	Habit	.196	1.522	.812	14.817
	Perceived Risk	.128	1.470	.232	2.004
	Social Interaction Anxiety	.020	.0182	.267	2.758

Tabelle 22: Formative indicator weights and loadings

Hypothesis	Path	β	S.E.	2.5% CI	97.5% CI	Result
H ₁	Push → Switching Intention	-.242	.090	-.419	-.066	Rejected
H ₂	Pull → Switching Intention	.422	.084	.250	.583	Supported
H ₃	Mooring → Switching Intention	-.442	.086	-.605	-.271	Supported
H ₄	Push × Mooring → Switching Intention	-.047	.082	-.211	.108	Rejected
H ₅	Pull × Mooring → Switching Intention	.048	.074	-.096	.196	Rejected
H ₆	Task Difficulty → Push	.848	.017	.812	.880	Supported
H ₇	Task Difficulty → Pull	.592	.047	.490	.678	Supported
H ₈	Task Difficulty → Mooring	-.520	.056	-.622	-.399	Supported
H ₉	Switching Intention → Switching Behavior	.461	.138	.196	.737	Supported
-	Age → Switching Intention	-.098	.053	-.204	.005	-
-	Gender → Switching Intention	.049	.056	-.059	.158	-
-	Industry: Retail → Switching Intention	.013	.068	-.122	.147	-
-	Industry: Telecommunication → Switching Intention	.025	.061	-.094	.144	-
-	Industry: Finance → Switching Intention	-.103	.061	-.224	.016	-

Tabelle 23: Structural model results

Note. R^2_{Push} : 71.7%, R^2_{Pull} : 34.3%, R^2_{Mooring} : 26.5%, $R^2_{\text{Switching Intention}}$: 36.5%, $R^2_{\text{Switching Behavior}}$: 6.5%, β : Path Coefficient, S.E.: Standard Error, CI: Confidence Interval

4.4.6 Discussion

This study advances the understanding of customer switching from CAs to HAs by applying and extending the PPM model in a longitudinal design. Several theoretical and practical implications emerge from the results.

4.4.6.1 Theoretical implications

First, the negative effect of the push factor on switching intention contrasts with the theoretical PPM assumption that the push factor should positively influence switching (Bansal et al., 2005). In this study, the push factor, primarily driven by dissatisfaction and perceived inefficiency, did not increase customers' likelihood of relying more on HAs. Instead, it reduced such intention. This suggests that when CA experiences are particularly negative, customers may not seek resolution through human support but may disengage from customer service altogether. In this context, the push factor appears to trigger an avoidance response rather than a substitution, thereby marking an important boundary condition for the PPM model in CA-HA switching. Interestingly, Li and Zhang (2023) report a similar pattern in the opposite direction, finding that push factors negatively affected switching intention from HAs to CAs, contrary to their hypothesis. Taken together, these findings suggest that in the domain of CA-HA switching, the push factor provokes avoidance rather than substitution, challenging conventional PPM expectations.

Second, the results confirm the positive effect of the pull factor, primarily driven by perceived usefulness, on switching intention. Customers who perceive HAs as useful are significantly more likely to plan to increase their reliance on them in the near future. This finding aligns with prior PPM research (e.g., Lenz et al., 2023) and underscores the relevance of positive destination-related expectations in shaping service switching.

Third, the results confirm the negative effect of the mooring factor, primarily driven by inertia, on switching intention. Customers who are attached to interacting with CAs are significantly less likely to plan an increased reliance on HAs in the near future. This finding is consistent with prior PPM research (e.g., Sun et al., 2017) and underscores the inhibiting role of the mooring factor in the PPM model. Notably, the mooring factor exerted a direct effect but did not moderate the relationships between the push and pull factors and switching intention. This absence of moderation suggests that in this context, the mooring factor acts as a direct barrier rather than a conditional influence.

Fourth, task difficulty emerges as a central antecedent that impacts all three PPM factors. When service interactions are perceived as particularly challenging, customers tend to experience stronger dissatisfaction and perceive the CA as inefficient, both of which intensify the push factor. At the same time, difficult tasks highlight the relative advantages of HAs, especially their effectiveness in resolving complex issues, which strengthens the pull factor. Finally, higher task difficulty reduces the inhibiting influence of the mooring factor, as customers become less bound by inertia that would otherwise keep them attached to CA use. Task difficulty, therefore, serves as a powerful contextual variable that can simultaneously intensify push and pull pressures, and weaken mooring barriers. Overall, this finding illustrates the potential of uncovering antecedents of the PPM factors, something that has rarely been done in empirical-quantitative PPM research (Marx, 2025).

Finally, this study provides rare longitudinal evidence for the intention-behavior link in PPM research. Switching intention significantly increases actual switching behavior, aligning with the broad theoretical perspective that intention is a reliable predictor of actual behavior (Ajzen, 1991) and meta-analytical evidence from PPM research (Marx, 2025). Nevertheless, the relatively low variance explained in behavior indicates that contextual constraints, such as the actual availability of HAs, company escalation policies, or the type of customers' service needs in the follow-up period, affect whether intentions translate into behavior.

4.4.6.2 Practical implications

For companies, the central challenge lies in balancing the efficiency gains of CAs with the risk of service breakdowns when CAs are unable to fulfill customer requests (Lu et al., 2024; Sands et al., 2020). The results of this study highlight several approaches to achieve this balance.

First, the finding that the push factor reduces switching intention suggests that negative CA experiences can cause customers to abandon customer service altogether, leaving problems unresolved. This poses a serious risk for companies, as unresolved service issues can escalate into relationship termination (Keaveney, 1995). The managerial implication is clear: customer service design must ensure that customers always have a viable resolution path before disengagement occurs. Therein, companies' policies for moving a customer from a CA to a HA play a decisive role. Customers often start with CAs, which is consistent with companies' goal of keeping service interactions efficient and low-cost (Lu et al., 2024; Sands et al., 2020). However, when the CA

cannot resolve the issue, the switch to a HA should be made as easy, transparent, and reliable as possible. Hidden or delayed options for contacting a HA at this stage risk losing customers at the moment when they most need support. By contrast, visible options such as a clearly labeled “chat/talk to a HA” button or proactive offers to transfer the interaction can keep customers engaged in the service process instead of dropping out.

Second, the important role of task difficulty in shaping all three PPM factors points to a valuable mechanism for managing this transition. If customers are asked at the outset to assess the perceived difficulty of their request, those with complex issues can be connected directly to HAs, preventing frustration with a CA that is unable to handle such requests effectively. Alternatively, the CA can automatically judge the difficulty of the task during the conversation and refer high-difficulty cases to HAs. Either approach reduces the likelihood of customers abandoning the service interaction altogether and helps ensure that difficult problems are resolved effectively.

Third, the positive effect of the pull factor, driven primarily by perceived usefulness, suggests that companies can actively highlight the effectiveness of HAs when CA interactions are not progressing well. Communicating that a HA can quickly and effectively resolve the issue may motivate customers to continue the service interaction with a human rather than abandoning it entirely. In this way, emphasizing the benefits of human support becomes a safeguard against dropout when customers grow frustrated.

Finally, the negative effect of mooring factor shows that many customers are already accustomed to starting service interactions with CAs and display inertia in continuing to use them. This is generally beneficial for companies, as it demonstrates that the CA-first approach is widely accepted (Lu et al., 2024). At the same time, it underscores the importance of ensuring that when CAs cannot provide satisfactory solutions, customers are guided smoothly toward human support. Companies should view customers’ inertia in using CAs as a strength, but they should still design processes that make switching to HAs simple and accessible when needed.

4.4.6.3 Limitations and future research

First, this study relies on a German convenience sample recruited through Clickworker. While this sample provides useful insights, it does not represent any specific population. Future research should seek to replicate the findings with representative samples from particular countries, industries or customer groups. In addition, cross-cultural comparisons would be valuable, as prior

research shows that service expectations can vary significantly across cultural contexts (Donthu & Yoo, 1998).

Second, the behavioral validation relies on self-reported switching behavior collected two months after the initial survey. While this two-wave design moves beyond purely cross-sectional studies, recall bias may have influenced participants' responses. Future research could complement self-reports with objective behavioral data, such as customer service logs, or employ experimental designs in which CA-HA switching is observed directly. In addition, mixed-method approaches such as follow-up interviews could provide richer insights into the motivations underlying switching decisions.

Third, the two-month follow-up period is somewhat arbitrary. While it aligns with recommendations from prior research (Bansal et al., 2005; Marx, 2025), switching dynamics are likely to unfold differently across individuals. Some participants may have switched during this interval but subsequently reverted to greater CA use, whereas others may need more time before altering their service usage patterns. Future research could examine alternative observation windows and employ longitudinal designs with shorter and repeated measurement intervals such as weekly surveys to capture the changes in switching behavior in greater detail.

Fourth, the study design relied on a retrospective critical incident approach, asking participants to recall a past CA interaction. This reliance on retrospective self-reports introduces the risk of memory distortions and a tendency to recall particularly salient or extreme experiences. Future research could employ experience-sampling methods, which prompt participants to document interactions in real time or shortly afterward, thereby reducing recall bias (Scollon et al., 2003). Another promising approach would be scenario experiments, in which participants are exposed to carefully designed service interactions with CAs and HAs in a controlled setting, allowing researchers to systematically manipulate conditions and directly observe switching decisions. Moreover, field studies in collaboration with service providers could further capture switching behavior as it naturally unfolds in customer service contexts.

Fifth, the push factor unexpectedly reduced switching intention, contrary to the theoretical assumptions of the PPM model. This finding suggests that the PPM model may not fully capture switching dynamics in contexts where disengagement is a viable response. PPM studies typically assume that customers choose between two alternatives, the incumbent and the new option, without

considering the possibility of withdrawing altogether (Bansal et al., 2005). In the case of CA-HA switching, however, disengagement is realistic: some customers may prefer to abandon their service issue entirely rather than invest additional effort in re-explaining their problem to a HA after a frustrating CA interaction. Li and Zhang (2023) observed a similar pattern in their study of HA-CA switching, which suggests that this result is not simply a methodological artifact. Therefore, future research should systematically investigate the conditions under which the push factor leads to disengagement rather than substitution.

4.4.7 Conclusion

This study examined why customers switch from CAs to HAs in customer service by applying the PPM model. The results show that switching is primarily driven by cognitive evaluations within the push and pull factors. Specifically, dissatisfaction and perceived inefficiency of CAs (push), along with the perceived usefulness of HAs (pull), emerged as the strongest determinants of switching. In contrast, affective qualities such as empathy proved insignificant, suggesting that the appeal of HAs in customer service is not rooted in emotions but in effectiveness. At the same time, inertia within the mooring factor strongly inhibited switching, as many customers are accustomed to starting service interactions with CAs and show resistance to change, even when human support is available. Task difficulty explained a substantial share of the variance in the PPM factors, highlighting that customers switch when CAs cannot manage demanding interactions. Actual behavior reveals that interest in HAs persists: two months after the first survey, 118 of 240 participants reported relying more on HAs than before.

Taken together, the findings underscore that the current competitive advantage of HAs lies in their ability to resolve complex service tasks. CAs still struggle with difficult requests, for example, due to limited understanding or restricted access to information, making human support indispensable. Over time, however, as CAs become capable of handling the full spectrum of customer demands, this advantage may erode. Thus, the continuing role of HAs in customer service may only be a temporary consequence of current technological limitations.

4.5 Beitrag 5: If it ain't broke, don't fix it? Understanding how an inertia mindset mitigates the effect of service failure on customer defection²⁰

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Keywords	Customer defection, Inertia mindset, Service failure
Status	Veröffentlicht

Tabelle 24: Kurzübersicht zu Beitrag 5

Quelle: Eigene Darstellung

4.5.1 Abstract

Implementing a customer relationship management (CRM) process can significantly improve a company's economic performance. However, the CRM process-economic performance link can be jeopardized by various moderating factors such as service failure. Against this background, the present study seeks to answer the question of whether a customer's inertia mindset can mitigate the effect of service failure on customer defection. To do this, we carried out an online survey including a one-factor between-subjects experimental design among 442 video streaming service customers. The results show that a customer's inertia mindset not only directly decreases defection intention, but also acts as a moderator by reducing the impact of service failure on defection intention. This finding has important implications for researchers and practitioners, which are further explored in this study.

4.5.2 Introduction

CRM combines relationship marketing strategies and relevant technology applications to establish, develop and maintain profitable, long-term relationships with well-chosen customers (Boulding,

²⁰ Eine gekürzte Version des Beitrags wurde bei der European Association of Consumer Research Conference im Jahr 2023 eingereicht und im Rahmen einer Poster-Session vorgestellt.

Staelin, Ehret, and Johnston, 2005; Payne & Frow, 2005). Companies that successfully implement a CRM process consisting of relationship initiation, maintenance, and termination can significantly improve their economic performance (Reinartz, Krafft, and Hoyer, 2004). However, the CRM process-economic performance link is impacted by various moderating and mediating factors that can be internal or external to a company (e.g., Ernst, Hoyer, Krafft, and Krieger, 2011; Reinartz et al., 2004). One such factor is service failure, as service failure is one of the main reasons why customers end their relationship with a company (de Matos, Henrique, and Rossi, 2007). As a result, companies have a high interest in understanding how to recover from service failure (de Matos et al., 2007), and identifying customer characteristics that moderate the impact of service failure on customer defection (e.g., de Matos, Rossi, Veiga, and Viera, 2009). This study strives to identify whether a customer's inertia mindset can be such a moderating characteristic. More precisely, we seek to answer the following research question: *Can a customer's inertia mindset mitigate the effect of service failure on customer defection?*

We chose video streaming services (VSS) as our research context to answer this question for three reasons: First, as customers have access to a wide variety of VSS (e.g., Amazon Prime Video, Disney+, Netflix) that offer different types of tempting content, they regularly defect and switch between VSS (Arkenberg, Ledger, Loucks, and Westcott, 2021). Second, in the context of VSS, there are various types of service failure (e.g., in-stream malfunctions, inaccessible content, lag, long startup times) that are common reasons why customers defect (Krishnan & Sitaraman, 2012). Third, VSS usually offer a subscription-based payment method, which means that maintaining stable customer relationships is essential to their strategy (Choi, Moss, Nading, Reasor, and Remley, 2021).

4.5.3 Theoretical Background and Hypotheses Development

To investigate whether a customer's inertia mindset can mitigate the effect of service failure on customer defection intention – defined as *a customer's intended behavior of decreasing or ceasing usage of a firm's offerings* (Henderson, Steinhoff, Harmeling, and Palmatier, 2021) – in the context of VSS, we derive a conceptual framework based upon status quo bias theory (Samuelson & Zeckhauser, 1988) and customer inertia marketing theory (Henderson et al., 2021). According to Henderson et al. (2021), a customer's inertia mindset can be defined as *a set of assumptions and beliefs that justify a disposition toward maintaining the status quo by eliminating the need to*

consider other options or form new intentions. Inert customers have an exaggerated preference for inaction, which makes them less likely to defect (Inman & Zeelenberg, 2002). We thus hypothesize that an inertia mindset decreases defection intention (**H₁**).

Henderson et al. (2021) identify thinking minimization and regret minimization as the two antecedents of an inertia mindset. Thinking minimization can be defined as *cognitive resource conservation biases that limit a customer from exerting effort to consider options and form intentions* (Henderson et al., 2021). Evaluating different alternative VSS is tiring for customers, which is why they often minimize thinking by adopting a “satisficing” strategy instead of an “optimization” strategy to conserve their cognitive resources (Bawa, 1990; Chernev, 2004; Shugan, 1980). In line with the common expression “if it ain’t broke, don’t fix it”, one such “satisficing” strategy could be to simply stick to the incumbent VSS. We thus assume that thinking minimization facilitates an inertia mindset (**H₂**).

Henderson et al. (2021) propose prior consumption consistency – defined as *the extent to which a customer’s consumption behaviors are stable over repeated occasions* – as an antecedent of thinking minimization. Because consistent consumption is more accessible in memory, it facilitates a customer’s natural inclination to minimize the cognitive effort required to make satisfactory decisions (Banerjee & Bandyopadhyay, 2003; Seethamaran, Ainslie, and Chintagunta, 1999). Thus, we hypothesize that prior consumption consistency increases thinking minimization (**H₃**).

Regret minimization can be defined as *ego-protective biases that limit a customer from noting or considering potentially superior counterfactuals to consumption behavior they feel responsible for enacting* (Henderson et al., 2021). Regret is a negative, cognitively based emotion that customers experience, when realizing or imagining that their present situation would have been better had they acted differently (Zeelenberg, 1999). Defecting from their current VSS would be a change with uncertain outcomes that customers are more likely to regret than the decision to maintain the status quo (Inman & Zeelenberg, 2002; Kim, 2013). We thus assume that regret minimization facilitates an inertia mindset (**H₄**).

Henderson et al. (2021) propose prior consumption magnitude – defined as *the extent to which a customer’s prior consumption behaviors are substantial* – as an antecedent of regret minimization. A greater magnitude of past actions causes a greater potential for regret, which customers seek to minimize (Arkes, Kung, and Hutzler, 2002; Buchanan, Summerville, Lehman, and Reb, 2016;

Tsiros, 2009). Thus, we hypothesize that prior consumption magnitude increases regret minimization (**H₅**).

A service failure can be defined as *a service performance that does not meet a customer's expectations* (Sparks & Fredline, 2007). Prior research has shown that the consequences of service failure include customer dissatisfaction (Hess, 2008), negative word-of-mouth (Weun, Beatty, and Jones, 2004), and customer defection (Keaveney, 1995). In line with previous research, we thus assume that service failure increases defection intention (**H₆**).

As previous research has shown, the longer customers remain with a company, the more likely they are to assume innocent causes for failure and suppress negative responses (Harmeling, Palmatier, Houston, Arnold, and Samaha, 2015). Likewise, inert customers will downplay the negative implications of a service failure because they seek to justify their disposition toward maintaining the status quo. Thus, we hypothesize that an inertia mindset weakens the positive relationship between service failure and defection intention (**H₇**).

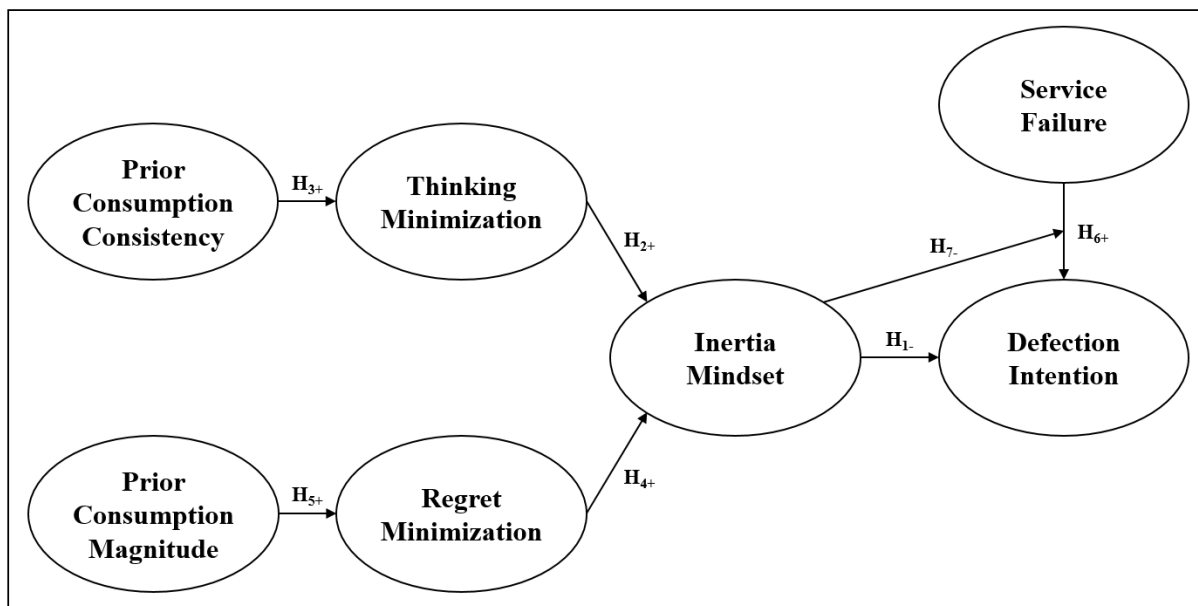


Abbildung 11: Research model

4.5.4 Method

4.5.4.1 Survey design

To test our hypotheses, we developed an online survey including a one-factor between-subjects experimental design. After a screening question and a brief introduction to VSS, we asked

participants to choose the VSS they currently use most, to which the survey subsequently referred [vss]. Thereafter, we surveyed the control variables (except for sociodemographics) and the research model's constructs. Hereafter, participants were randomly assigned to one condition (service success vs. service failure) displaying a scenario in which they experience an interaction with their VSS that either ends in success or failure. After that, we surveyed the dependent variable and sociodemographics. The scenarios were created based on previous literature (e.g., Hess et al., 2007). To circumvent comprehension issues with the scenarios and the survey in general, we conducted a cognitive pretest with 5 participants using the "think-aloud" method (Charters, 2003). Furthermore, we carried out a quantitative pretest with 34 participants to confirm scale reliability and validity as well as the perceived appropriateness and realism of the scenarios (Bagozzi et al., 2016). The results confirmed the suitability of the scenarios in this regard. Finally, the participants' perceptions regarding the service outcome (success vs. failure) were measured using the item "How would you rate the performance of the service encounter?" (scale ranging from (1) "very bad" to (5) "very good"). A Welch's unequal variances t-test confirmed that performance was perceived to be significantly better in the success condition than in the failure condition ($M_{\text{success}}=4.10$, $SD_{\text{success}}=0.73$, $M_{\text{failure}}=2.09$, $SD_{\text{failure}}=0.89$, $t=26.05$, $p<0.01$).

4.5.4.2 Sample

Participants using at least one VSS were recruited from the crowd-working platform Clickworker (<https://www.clickworker.de/>). To ensure high data quality, we applied a rigorous data cleaning process. Starting with 551 fully completed surveys, we first removed participants (-67) who failed at least one of the three methodologically different attention checks that were built into the survey at different stages (Aguinis, Villamor, and Ramani, 2021). Second, we removed participants (-42) based on their completion time for the survey using a relative speed index of 2 as the maximum threshold (Leiner, 2019). This results in a final sample of 442 participants ($M_{\text{age}}=39.26$, $SD_{\text{age}}=11.45$, 76.70% male).

4.5.5 Results

4.5.5.1 Measurement model

The hypotheses were tested via covariance-based structural equation modeling in R (version 4.2.2) using the lavaan package (version 0.6.12). We follow the approach recommended by Anderson and Gerbing (1988) by first applying confirmatory factor analysis (CFA) to assess the measurement

model, followed by the assessment of the structural model. Given that not all variables were normally distributed, we use the robust Satorra-Bentler scaled statistics for goodness-of-fit testing of both the measurement and the structural model to obtain more accurate results (Hu, Bentler, and Kano, 1992).

To measure the research model's constructs we adapted established scales from previous research (Henderson et al., 2021). Both inertia mindset ("When it comes to my status quo usage of [vss] versus other options, I feel 'if it ain't broke, don't fix it'.") and defection intention ("How likely are you to cancel your [vss] subscription over the next six months?") were measured with a single item. To validate the measurement model, we tested construct reliability and validity. The results (Table 1 [hier: Tabelle 25]) show that all Cronbach's α values exceed the recommended level of 0.7 (Nunnally, 1978), that all average variances extracted (AVE) meet the 0.5 cutoff required (Fornell & Larcker, 1981), and that composite reliabilities (CR) for each multi-item construct are greater than the recommended threshold of 0.6 (Bagozzi & Yi, 1988). Furthermore, the square roots of the AVE exceed the interconstruct correlations, indicating discriminant validity (Fornell & Larcker, 1981). Overall, the CFA model fits the data well ($\chi^2/d.f.=2.269$; RMSEA=.054; SRMR=.030; TLI=.970; CFI=.980). Common method bias (CMB) was tested employing the marker variable technique (Malhotra, Kim, and Patil, 2006). The results suggest that CMB does not pose a problem in this study.

#	Constructs	α	AVE	CR	Correlations/Square Roots of AVE					
					1	2	3	4	5	6
1	Prior Consumption Consistency	.831	.712	.831	.844					
2	Prior Consumption Magnitude	.933	.881	.937	.401	.939				
3	Thinking Minimization	.921	.755	.928	.196	.195	.869			
4	Regret Minimization	.927	.812	.928	.053	.106	.293	.901		
5	Inertia Mindset	n/a	n/a	n/a	.213	.067	.415	.304	n/a	
6	Defection Intention	n/a	n/a	n/a	-.327	-.249	-.215	-.015	-.164	n/a

Tabelle 25: Assessment of the measurement model

4.5.5.2 Structural model

The structural model (Table 2 [hier: Tabelle 26], Model 1) shows a good overall model fit ($\chi^2/d.f.=2.417$; RMSEA=.057; SRMR=.088; TLI=.956; CFI=.967). The results (Table 2 [hier: Tabelle 26], Model 1) show that thinking minimization ($\beta=.366$, $p<.01$, H₂) and regret minimization ($\beta=.209$, $p<.01$, H₄) foster an inertia mindset, which has a negative effect on defection

intention ($\beta=-.129$, $p<.01$, H_1). Moreover, the results indicate a positive effect of prior consumption consistency on thinking minimization ($\beta=.213$, $p<.01$, H_3) and a positive effect of prior consumption magnitude on regret minimization ($\beta=.109$, $p<.05$, H_5). With regards to H_6 , we find that service failure significantly increases defection intention ($\beta=.271$, $p<.01$, H_6). Finally, the results show that the interaction term of inertia mindset and service failure exerts a negative influence on defection intention ($\beta=-.101$, $p<.05$, H_7), which supports H_7 . To account for potential other explanations, we control for the perceived attractiveness of alternative VSS, relationship quality, age, gender, and income. The results (Table 2 [hier: Tabelle 26], Model 2) show that all hypothesized effects remain significant.

Hypothesis	Path	Model 1	Model 2
<i>Hypothesized paths:</i>			
H ₁	IM → DI	-.129 (.046) ***	-.096 (.043) **
H ₂	TM → IM	.366 (.060) ***	.366 (.060) ***
H ₃	PCC → TM	.213 (.062) ***	.218 (.061) ***
H ₄	RM → IM	.209 (.050) ***	.209 (.050) ***
H ₅	PCM → RM	.109 (.079) **	.109 (.079) **
H ₆	SF → DI	.271 (.144) ***	.276 (.140) ***
H ₇	(IM*SF) → DI	-.101 (.090) **	-.097 (.085) **
<i>Control variables:</i>			
-	AA → DI	-	.097 (.060) **
-	RQ → DI	-	-.181 (.058) ***
-	Age → DI	-	.037 (.074)
-	Gender → DI	-	.049 (.170)
-	Income → DI	-	-.043 (.026)

Tabelle 26: Assessment of the structural model

Notes: $R^2_{DI}=21.7\%$ (Model 1), $R^2_{DI}=26.1\%$ (Model 2)

* $p<.1$, ** $p<.05$, *** $p<0.01$; Standardized beta coefficients with standard errors in parentheses

IM: Inertia Mindset, DI: Defection Intention, TM: Thinking Minimization, PCC: Prior Consumption Consistency, RM: Regret Minimization, PCM: Prior Consumption Magnitude, SF: Service Failure, AA: Alternative Attractiveness, RQ: Relationship Quality

4.5.6 Discussion and Implications

The purpose of this study was to answer the question of whether a customer's inertia mindset can mitigate the effect of service failure on customer defection. Therein, our research makes two important contributions to the literature. First and most importantly, we confirm that an inertia mindset not only directly decreases defection intention, but also reduces the impact of service failure on defection intention. Thereby, we answer a call for research by Henderson et al. (2021) to apply an inertia perspective to negative shocks, including service failures. Researchers might use this finding as a starting point to further uncover the important moderating role of an inertia mindset in governing stable customer relationships. Moreover, companies could harness this insight to optimize their service recovery management in the event of a service failure (Craighead, Karwan, and Miller, 2004). Knowing that an inertia mindset emerges from prior consumption consistency and magnitude, companies can segment their customers accordingly. Customers with low prior consumption consistency and magnitude are less likely to be inert and in turn more likely to defect in the event of a service failure. Thus, companies should focus their scarce service recovery resources on these customers. Given that companies likely already have the required data available (e.g., number of months a customer has been a subscriber as an indication of prior consumption magnitude), this could be an easy-to-implement change with a potentially high upside. Second, by confirming the findings of Henderson et al. (2021) in a new research context, we increase the external validity of the emerging customer inertia marketing theory (Winer, 1999).

4.5.7 Limitations and Future Research

The study's findings highlight new avenues for future research. First, it would be insightful to replicate the results in new research contexts, different cultures, and with representative samples. Second, future research could use panel data to examine how an inertia mindset evolves over time. Third, we measured customers' defection intentions in this study. However, while intentions are generally the best predictor of behavior, they only translate into actual behavior under certain conditions (Ajzen, 1991). Thus, future research could use field studies to circumvent the intention-behavior gap. Finally, our study uses a scenario-based approach to manipulate service failure. Although our results show that the manipulations had the desired effects and that the scenarios were perceived as realistic, it would be insightful – albeit difficult – to gather data on real service failures and their impact on customer defection.

4.6 Beitrag 6: Enhancing virtual reality experiences in grocery retailing: The impact of audio priming on spatial presence and retailer outcomes

Autoren	Tobias Marx, Giulian Welle, Nadine R. Gier-Reinartz
Zitation	Marx, T., Welle, G., & Gier-Reinartz, N. R. (2025). Enhancing virtual reality experiences in grocery retailing: The impact of audio priming on spatial presence and retailer outcomes. <i>The International Review of Retail, Distribution and Consumer Research</i> , 1–25.
URL	https://doi.org/10.1080/09593969.2025.2512303
Keywords	Virtual reality, Priming, Spatial presence, Virtual farm tours, Laboratory experiment
Status	Veröffentlicht

Tabelle 27: Kurzübersicht zu Beitrag 6

Quelle: Eigene Darstellung

4.6.1 Abstract

As omnichannel retail strategies increasingly blend virtual and physical experiences, retailers are recognizing the significant potential of virtual reality (VR). Considering the crucial role of spatial presence in determining the quality of VR experiences, this study explores novel ways to increase spatial presence, particularly for virtual tours as a digital in-store technology in grocery retail. Given a lack of research on priming in the context of VR, the goal of this study is to examine the impact of audio priming on spatial presence. Additionally, we explore the relationship between spatial presence and perceived enjoyment, as well as between perceived enjoyment and key pre-economic variables relevant to grocery retailers. The hypotheses are developed based on theoretical backgrounds in VR, spatial presence, fluency theory, and priming. To test our hypotheses, we conducted a one-factor between-subjects experiment involving 60 participants divided into one control and two treatment groups. Before participating in a virtual farm tour, each treatment group was exposed to a distinct audio priming stimulus focusing either on farm ambiance or VR technology. The results show significant differences in spatial presence among the groups. While priming participants on VR technology enhanced spatial presence, priming them on farm ambiance had no effect. Technology priming prevents consumers from experiencing a technology shock by familiarizing them with the technological aspects of the VR experience, increasing processing

fluency. In contrast, ambiance priming relies on consumers' pre-existing associations, which may not align with the actual VR experience, disrupting processing fluency. Furthermore, the results show that the increased spatial presence results in greater perceived enjoyment, which ultimately leads to an increased recommendation intention and attitude toward the retailer. Therein, this study highlights the potential of integrating audio priming in VR applications, specifically advocating for its strategic use in grocery retail settings to enhance consumer experiences in omnichannel environments.

4.6.2 Introduction

As omnichannel retail strategies increasingly blend virtual and physical experiences, retailers around the world are recognizing the significant potential of virtual reality (VR) and are progressively investing capital to take advantage of advancements in this field (Yoo et al. 2023). Whether it is the Swedish furniture retailer IKEA (IKEA VR), the Chinese e-commerce giant Alibaba (Buy+), or Europe's largest consumer electronics retailer (Virtual SATURN)—they have all tested opportunities to create additional value for consumers in VR (Peukert et al. 2019). By successfully establishing virtual stores, retailers can extend their reach by allowing consumers from distant locations to visit virtually (Yoo et al. 2023). However, opportunities extend beyond the establishment of new distribution channels, encompassing novel approaches to create consumer experiences, coupled with the potential to leverage the virtual environment as a marketing instrument (Dwivedi et al. 2023; Yoo et al. 2023).

For instance, virtual tours enabled by VR technology present an opportunity for retailers to provide unique consumer experiences—whether in physical or virtual stores. Prior research has shown promising results for virtual tours as a marketing instrument, suggesting that, for example, virtual farm tours offer a viable method to engage a vast audience, irrespective of a farm's physical location (Schütz, Kurz, and Busch 2022). These tours capture the essence and presence of an in-person farm tour while minimizing the time and effort required by participants (Asani et al. 2019; Schütz, Kurz, and Busch 2022). Furthermore, in light of declining public trust in intensive animal production systems in many European countries (European Commission 2015; Krystallis et al. 2009; Weible et al. 2016), consumers without first-hand knowledge of farming operations desire a greater understanding of agricultural practices and demand transparency (Boogaard et al. 2011; Vanhonacker et al. 2008). Providing visual insights into livestock stables through farm tours can

increase transparency, improve animal welfare perceptions, and potentially stimulate a more sustainable food shopping behavior (Blokhuis et al. 2003; Schütz, Kurz, and Busch 2022; Ventura et al. 2016). Recognizing consumers' growing demand for transparency, some grocery retailers have already taken action. For example, REWE introduced livestreams and VR headsets at the point of sale in 2018 in one of its supermarkets to provide visual insights into livestock stables and has continued using them since, underscoring their ongoing relevance to consumers (REWE Richrath 2018; Kletschke²¹ 2019; Schütz, Kurz, and Busch 2022). By not utilizing this opportunity, grocery retailers miss the chance to communicate their own representation of production systems, leaving consumers exposed solely to media portrayals, which tend to shape public perception (Tonsor and Wolf 2012). A key barrier to broader implementation of virtual farm tours may be the concern among grocery retailers that visual depictions of production processes could provoke negative reactions from consumers, as the imagery might diverge from their idealized animal welfare expectations (Christoph-Schulz et al. 2018). Consequently, it is essential to ensure that virtual tours, which, unlike in-person tours, may be conducted without appropriate guidance and context, are well received by consumers. Understanding how to effectively introduce consumers to virtual farm tours is therefore critical to creating a high-quality, standalone VR experience.

The quality of a VR experience generally depends on the degree of immersion and the subsequent spatial presence. Spatial presence is a key construct in virtual reality, and researchers and practitioners are actively seeking ways to enhance it (Cummings and Bailenson 2016). So far, only one study (Cerdeira et al. 2021, using visual priming) has explored priming's effect on spatial presence, showing that priming can indeed increase spatial presence. Given the frequent use of priming and its significant effects in other research domains (e.g., Lee and Labro 2004; North, Sheridan, and Areni 2016), we investigate whether audio priming can enhance spatial presence during VR experiences. Audio priming generally refers to *the use of auditory stimuli to activate desired concepts in an individual's mind and influence their response to a subsequent stimulus* (Bargh and Chartrand 1999). In this study, audio priming was employed prior to a virtual farm tour to enhance how participants perceived the VR experience, using either an audio stimulus related to farm ambiance or one related to VR technology. Additionally, we aim to explore the relationship

²¹ In der veröffentlichten Version des Beitrags wird der Autorenname versehentlich als „Kletsche“ wiedergegeben. Die korrekte Schreibweise lautet „Kletschke“.

between spatial presence and perceived enjoyment, which then translates into key pre-economic variables relevant to retailers. More precisely, we seek to answer the following research questions:

- (1) Does audio priming increase spatial presence?
- (2) Does spatial presence increase perceived enjoyment?
- (3) Does perceived enjoyment increase recommendation intention and attitude toward the retailer?

By answering these questions, this study makes several key contributions: First, it extends research on VR experiences by being the first to introduce audio priming as a novel mechanism to enhance spatial presence. Specifically, we empirically demonstrate that technology priming enhances spatial presence, whereas ambiance priming does not, and we provide a theoretical explanation for these effects by integrating fluency theory. Second, our findings establish positive relationships between spatial presence, perceived enjoyment, and key consumer responses relevant to grocery retailers, namely recommendation intention and attitude toward the retailer. Finally, we offer actionable guidance for grocery retailers on leveraging audio priming to optimize VR experiences.

The rest of this paper is organized in the following manner: The second chapter presents the theoretical background, hypotheses development, and conceptual framework. The third chapter outlines our methodological approach. The results are revealed in the fourth chapter. The fifth chapter discusses the results, highlighting their theoretical and practical significance. Lastly, the sixth chapter outlines the limitations of this study and proposes directions for future research.

4.6.3 Theoretical background

4.6.3.1 Virtual reality, immersion, and spatial presence

The term VR refers to *an artificial, virtual, and viewer-centered experience in which users are at least visually isolated from their physical environment in an all-encompassing three-dimensional space* (Rauschnabel et al. 2022). VR experiences are typically facilitated through VR headsets, which obscure the user's surroundings while presenting information depicting a virtual environment (Rauschnabel et al. 2022). VR headsets were originally designed for gaming and entertainment, but their usage has gradually expanded to include areas such as job training, prototyping, marketing, and tourism (Shahab, Ghazali, and Mohtar 2021). Researchers have investigated the use of VR across multiple commercial sectors, including retail (e.g.,

Krasonikolakis et al. 2018; Sina and Wu 2023; Vrechopoulos, Apostolou, and Koutsouris 2009), the fashion industry (e.g., Yaoyuneyong et al. 2018), manufacturing (e.g., Berg and Vance 2017), tourism (e.g., Lee et al. 2019; Wei, Qi, and Zhang 2019), and healthcare (e.g., Fertleman et al. 2018).

The quality of a VR experience generally depends on the degree of immersion and the subsequent spatial presence (also referred to as physical presence in Lee 2004 or telepresence in Draper, Kaber, and Usher 1998; Rauschnabel et al. 2022), which describes *the psychological sense of 'being there' in the virtual environment* (Hartmann et al. 2016; Heeter 1992; Slater and Wilbur 1997; Markowitz et al. 2018). The terms immersion and spatial presence are often mistakenly used as synonyms. In line with numerous researchers in this field (e.g., Cummings and Bailenson 2016; Peukert et al. 2019; Schultze and Orlikowski 2010; Sharda et al. 2004; Slater and Wilbur 1997), our understanding is that immersion is not a subjective feeling, but an objective measure. Spatial presence, on the other hand, is the human perception of a virtual environment (Schultze and Orlikowski 2010). Immersion (technology), among other factors, leads to spatial presence (perception) (Cummings and Bailenson 2016; Schultze and Orlikowski 2010; Sharda et al. 2004). Both researchers and practitioners have been exploring various options to increase spatial presence (Cummings and Bailenson 2016).

4.6.3.2 Fluency theory

Processing fluency refers to *the ease with which an individual processes a stimulus* (Reber, Schwarz, and Winkielman 2004; Schwarz 2004). The core proposal of fluency theory is that the more fluently a stimulus is processed, the more positive the individual's response (Reber, Schwarz, and Winkielman 2004).

High fluency feels good to individuals for numerous reasons, including its association with progress toward successful recognition of the stimulus, error-free processing, the availability of appropriate knowledge structures to interpret the stimulus, and its signaling that the external stimulus is familiar and thus unlikely to be harmful (Carver and Scheier 1990; Derryberry and Tucker 1994; Fernandez-Duque et al. 2000; Schwarz 1990; Simon 1967; Ramachandran and Hirstein 1999; Vallacher and Nowak 1999; Zajonc 1968; 1998).

Fluency theory is particularly relevant in the context of this study, because it highlights the crucial role of ease of processing in creating engaging and effective consumer experiences. In a highly

stimulated retail environment, where consumers are constantly exposed to competing stimuli, ensuring that consumer experiences are processed fluently is essential for enhancing acceptance and engagement (Im and Ha 2018; Xiao and Tan 2024). If the experience is difficult to process, consumers may disengage. Moreover, when introducing a new consumer experience, such as a virtual farm tour, the extent to which consumers can effortlessly process the experience impacts its effectiveness (Jiang, Guan, and de Haaij 2020).

According to Reber, Schwarz, and Winkielman (2004) and Winkielman et al. (2012), processing fluency can be influenced by various factors, including contrast, clarity, presentation duration, prior exposure to the stimulus, and priming. Moreover, a neural experimental study by Gottfried and Dolan (2003) demonstrated that congruity between stimuli increases processing fluency, a finding later reinforced by a survey-based experiment conducted by Jiang, Guan, and de Haaij (2020) in the context of online video advertising.

4.6.3.3 Priming

Priming can be defined as *a phenomenon where exposure to one stimulus can activate desired concepts in an individual's mind to influence the response to a subsequent stimulus* (Bargh and Chartrand 1999). The concept of priming is rooted in the associative network model of memory, which posits that ideas, words, and concepts are stored in the brain in a network of interconnected nodes. When one node is activated, related nodes are also likely to be triggered, facilitating the recall or recognition of associated information. This activation process is the basis of priming. Exposure to a preliminary stimulus, also known as a prime, influences the reaction to a subsequent stimulus by activating related associations (Collins and Loftus 1975).

The lack of research on priming in the context of VR is particularly noteworthy, given that numerous studies have consistently shown the importance of priming as a concept in consumer research using various stimuli. For example, Nedungadi (1990) examined how priming consumers with brand names influences the likelihood of brand choice, Mandel and Johnson (2002) investigated how background images and colors of a web page affect consumers' product choice, and Lee and Labroo (2004) examined how conceptual and perceptual fluency affect brand evaluation. Therein, most research has focused on visual priming. However, there are also numerous studies on audio priming (e.g., North, Hargreaves, and McKendrick 1999; North, Sheridan, and Areni 2016), highlighting its potent influence on consumer behavior.

A crucial aspect of priming is its cross-modal capability. Cross-modal priming implies that a stimulus encountered through one modality can trigger related concepts or associations within an entirely distinct modality (Vallet, Brunel, and Versace 2010). For example, the color of a beverage (i.e., visual modality) can affect how sweet it is perceived to taste (i.e., gustatory modality), even if the actual flavor remains unchanged (Hoegg and Alba 2007). Similarly, Williams and Bargh (2008) discovered that individuals who briefly held a cup of hot coffee judged a target person as having a warmer (generous, caring) personality, while Liljenquist Zhong, and Galinsky (2010) demonstrated that the scent of cleanliness can induce charitable behavior. In this respect, there is ample reason to assume that audio priming influences spatial presence.

4.6.3.4 Hypotheses development and conceptual framework

To answer our research questions, we derive hypotheses based on the previous theoretical considerations and the extant body of literature. Fluency theory suggests that priming can increase processing fluency, leading to a more positive response to the stimulus due to the sense of familiarity it creates (Reber, Schwarz, and Winkielman 2004). Audio priming can shape consumers' understanding of an environment and create an association between what they hear and what they expect to experience (Bolivar, Cohen, and Fentress 1994; Gaver 1993; North, Hargreaves, and McKendrick 1999). In the context of a VR experience, providing an audio prime that resonates with the upcoming visual content should increase consumers' sense of familiarity, leading to an elevated spatial presence (Cerda et al. 2021; Sjölie 2012). This alignment between auditory and visual stimuli could be particularly impactful if the audio provides context prior to the experience, effectively setting the stage for what is to come (Cerda et al. 2021; Lombard and Ditton 1997). Regarding virtual farm tours, we hypothesize there are two possible contexts for audio priming to potentially enhance consumers' spatial presence: the ambiance of a farm and the technology behind the VR experience. These specific types of audio priming were chosen based on a qualitative study by Schütz, Kurz, and Busch (2022), in which participants were interviewed after partaking in a virtual farm tour. The rationale for each type of priming is explicated in the development of the respective hypotheses.

To prepare participants for a farm-themed VR experience, it might be helpful to introduce them to the ambiance of a real farm. Prior qualitative research by Schütz, Kurz, and Busch (2022) found that consumers from urban areas, who may have never visited a farm or seen the inside of a stable,

perceived virtual farm tours as an accessible way to gain such experiences. However, transitioning, for instance, from the inside of a supermarket in a city center to a virtual farm environment may feel abrupt and unfamiliar for these consumers. Ambiance priming can help bridge this gap by familiarizing participants with the sensory aspects of a farm before the VR experience begins, making the transition smoother and reducing potential confusion, disorientation, or unfamiliarity (Cerda et al. 2021; Sjölie 2012), thereby increasing processing fluency. Therefore, we hypothesize that audio priming consumers on farm ambiance has a positive effect on their spatial presence during virtual farm tours (**H_{1a}**). In a similar vein, priming consumers on the technology behind the VR experience could serve as a way to enhance their spatial presence. Prior qualitative research by Schütz, Kurz, and Busch (2022) found that consumers who participated in virtual farm tours reported unfamiliarity with the VR experience—including a feeling of disorientation—as a key barrier to implementation at the point of sale. This suggests that processing the virtual environment may be challenging, especially for first-time users but also for those with prior experience, potentially leading to a technology shock that reduces spatial presence. Technology priming can address this issue by providing consumers with an explanation of what to expect and familiarizing them with the technological aspects of the VR experience, such as the specifics of the VR headset or the mechanics behind a 360-degree video. This preparation helps them become more comfortable with the VR medium itself and experience a smoother transition from the real world to the virtual farm tour, mitigating potential confusion, disorientation, or unfamiliarity (Cerda et al. 2021; Sjölie 2012), thereby increasing processing fluency. Thus, we hypothesize that audio priming consumers on VR technology has a positive effect on their spatial presence during virtual farm tours (**H_{1b}**).

Beyond the impact of audio priming on spatial presence, it is important to understand how spatial presence impacts perceived enjoyment, which then translates into key pre-economic variables relevant to retailers. Perceived enjoyment, in the context of VR experiences, can be defined as *a positive affective response to a VR experience in its own right, apart from any anticipated consequences* (Davis, Bagozzi, and Warshaw 1992; Vorderer, Klimmt, and Ritterfeld 2004). Theoretical considerations from previous research suggest that spatial presence within a virtual environment leads to higher perceived enjoyment (Heeter 1995; Lombard and Ditton 1997; Tamborini and Skalski 2006). Furthermore, numerous empirical studies have shown a positive correlation between spatial presence and perceived enjoyment (Nah et al. 2011; Peukert et al. 2019;

Sylaiou et al. 2010). In line with previous research, we thus hypothesize that spatial presence has a positive effect on perceived enjoyment (**H₂**).

Recommendation intention in the context of this study can be defined as *a consumer's intention to recommend the virtual farm tour to a friend or colleague* (Ajzen 1991). Intentions are generally considered the best predictor of behavior if requisite opportunities and resources are available (Ajzen 1991). In marketing practice, a key metric among companies developed by Reichheld (2003) is the net-promoter score (NPS). The NPS assesses customer loyalty by asking respondents how likely they are to recommend a company to others, classifying them into promoters and detractors based on their responses, and calculating the ratio of promoters to detractors, essentially measuring recommendation intention at the customer base level. In general, consumers like to recommend enjoyable experiences to others, because they seek approval and positive recognition (Hennig-Thurau et al. 2004). Furthermore, prior empirical research suggests a positive relationship between perceived enjoyment and recommendation intention (Yousaf et al. 2021). Thus, we hypothesize that perceived enjoyment has a positive effect on recommendation intention (**H₃**).

Attitude toward the retailer can be defined as *a learned predisposition to respond in a consistently favorable or unfavorable manner toward the retailer* (Ajzen 1991; Mackenzie and Lutz 1989). According to Ajzen and Fishbein (1980), an individual's attitude toward an object is determined by the multiplicative relationship between (1) the probability that the individual believes the object has a certain attribute and (2) the individual's evaluation of that attribute within the object. In our case, the object of attitude formation is the retailer. In the context of our study, individuals learn to associate a new attribute with the retailer, namely that the retailer has introduced the possibility of experiencing virtual farm tours in its stores. If this new attribute is evaluated positively (i.e., if individuals enjoy the virtual farm tour), the attitude toward the retailer will improve. Based on these considerations, we hypothesize that perceived enjoyment has a positive effect on attitude toward the retailer (**H₄**). Figure 1 [hier: Abbildung 12] illustrates our conceptual framework.

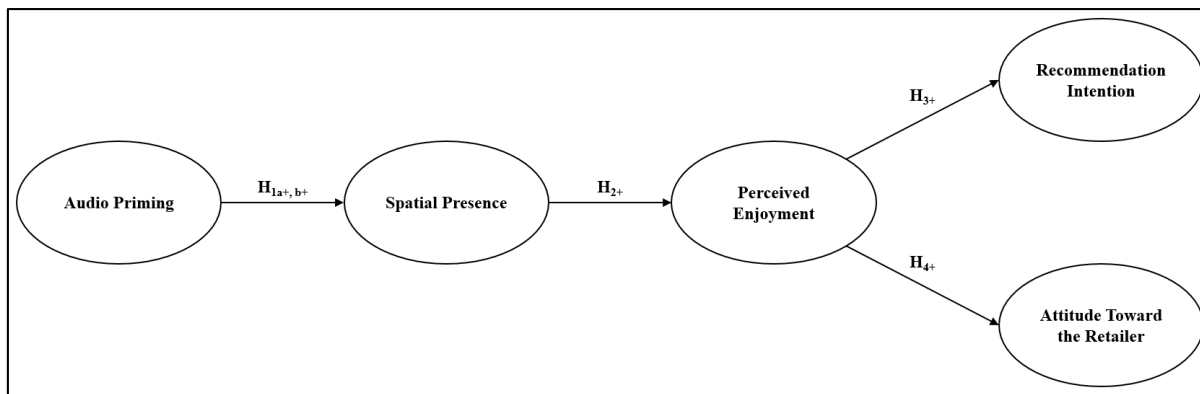


Abbildung 12: Conceptual framework

4.6.4 Method

4.6.4.1 Preliminary study

In preparation for our main study, we undertook a preliminary study to validate our two distinct audio priming stimuli. We developed these stimuli based on insights from literature on guided imagery. According to Dinger-Broda (2013), a guided imagery session consists of three distinct phases: 1. Induction Phase: This phase helps participants enter a relaxed state by focusing on their breathing and achieving physical relaxation, which is essential for engaging in the main phase; 2. Main Phase: This phase delivers the desired stimulus, which in our study involved either the farm ambiance or the VR technology priming; 3. Return Phase: In this phase, participants are gently brought back to a wakeful, alert state through deep breathing and movement. The stimuli, articulated in German, were matched in length both in written format and spoken duration (Farm ambiance: 1364 characters, 2 minutes and 18 seconds (Group 1); VR technology: 1361 characters, 2 minutes and 17 seconds (Group 2); for the full stimuli, refer to the Appendix). Our objective was to ascertain consistent voice quality and general attitude toward the audio content across both stimuli.

To conduct our preliminary study, we developed an online survey that was distributed through the crowdworking platform Clickworker (<https://www.clickworker.de/>). To ensure high data quality, we applied a rigorous data cleaning process. Starting with 100 completed surveys (50 for each group), we first removed participants who failed at least one of two methodologically different attention checks that were built into the survey at different stages (Aguinis, Villamor, and Ramani 2020). Second, we removed participants based on their completion time for the survey using a

relative speed index of 2 as the maximum threshold (Leiner 2019). Finally, we excluded participants with the most extreme scores on the gamma factor scale of socially desirable response behavior, which indicates a tendency either to diminish negative qualities or overemphasize positive qualities (Kemper et al. 2012). This resulted in a final sample of 86 participants ($N_{G1}=45$, $N_{G2}=41$, $M_{age}=41.16$, $SD_{age}=11.66$, 65.1% male).

Perceived voice quality was measured with a seven-point semantic differential scale ranging from -3 to 3, developed by Nieboer, de Graaf, and Schutte (1988). Likewise, attitude toward the audio content was measured with a seven-point semantic differential scale ranging from -3 to 3, adapted from Donthu (1998). A Welch's unequal variances t-test confirmed that there were no significant differences between the two groups in terms of perceived voice quality ($M_{G1}=.30$, $SD_{G1}=.75$, $M_{G2}=.19$, $SD_{G2}=.68$, $t=.708$, $p=.481$) or attitude toward the audio content ($M_{G1}=.42$, $SD_{G1}=1.07$, $M_{G2}=.25$, $SD_{G2}=.82$, $t=.816$, $p=.417$).

4.6.4.2 Main study

Upon entering the research facility, participants were briefed about the study's procedure. They were then familiarized with the VR headset, with explanations of its operation and functionality. Participants then completed a pre-questionnaire covering socio-demographics, previous experience with VR headsets, measured on a five-point scale ("Do you have experience using VR headsets?", 1=none, 5=very much), and farm tours, assessed with a binary scale ("Have you ever participated in a farm tour?", 0=no, 1=yes). The questionnaire also included the gamma factor scale of socially desirable response behavior (Kemper et al. 2012), measured on a five-point Likert scale (1=does not apply at all, 5=fully applies), the short version of the Positive and Negative Affect Schedule (PANAS) developed by Mackinnon et al. (1999), measured using a five-point Likert scale (1=not at all, 5=very much), and the Spontaneous Use of Imagery Scale (SUIS) developed by Reisberg et al. (2003), measured on a five-point Likert scale (1=never applicable, 5=always fully applicable).

Subsequently, participants in the experimental groups received their designated audio priming stimulus. For procedural consistency, the control group was provided with basic audio instructions. However, since the control group did not receive a priming stimulus, the induction and return phases outlined in the previous chapter were not applicable (for the full instructions, refer to the Appendix). All audio was delivered to participants via Bluetooth-connected Apple AirPods, set to a consistent volume level of 8. Participants then started the virtual farm tour, which was the same

for all groups. They began by standing in front of a barn. Using the VR headsets' eye-tracking technology, they were able to enter the barn by focusing on the door. Participants then watched a 360-degree video of the barn from three different perspectives. After the video, they found themselves outside the barn again. The virtual farm tour was facilitated using the Pico G2 4K VR headset.

According to Rauschnabel et al. (2022), VR applications can generally be positioned on a continuum based on spatial presence, ranging from atomistic (low spatial presence) to holistic (high spatial presence). The position along the continuum is influenced by several factors, including the degrees of freedom (DoF), where a key differentiation is commonly drawn between 3 DoF and 6 DoF. VR headsets with 3 DoF offer an experience characterized by rotational tracking. This feature allows users to look around by turning their head in any direction, while their position within the virtual environment remains static. On the other hand, VR headsets with 6 DoF offer a richer experience by incorporating both rotational and translational tracking. This dual tracking capability allows users to move or walk around in the virtual space and turn their heads in any direction (Pan and Hamilton 2018). The Pico G2 4K VR headset, which was utilized to display the 360-degree video in our study, featured 3 DoF.

Concluding the virtual farm tour, a short audio snippet informed participants that their virtual journey had ended, instructing them to remove the VR headset. Immediately afterward, participants received the post-questionnaire, which again included the short version of the PANAS developed by Mackinnon et al. (1999), as well as the variables from our conceptual framework. Spatial presence was measured using the Spatial Presence Experience Scale (SPES) developed by Hartmann et al. (2016), which models spatial presence as a reflective-reflective higher-order construct (Sarstedt et al. 2019) consisting of two dimensions, measured with four items per dimension: self-location (SPES-SL) and possible actions (SPES-PA). Both dimensions were assessed on a five-point Likert scale (1=fully disagree, 5=fully agree). To measure attitude toward the retailer, participants were asked to imagine that EDEKA, Germany's largest grocery retailer by market share, introduced the possibility of experiencing virtual farm tours in its stores. Participants were then asked to rate their attitude toward EDEKA on a seven-point semantic differential scale ranging from -3 to 3, using three items developed by Muehling (1987) and MacKenzie and Lutz (1989). Perceived enjoyment was measured with a single item using a five-point Likert scale (1=not at all, 5=very much), and recommendation intention was assessed with a single item on a ten-point

Likert scale (1=very unlikely, 10=very likely). Once the participants had completed the study, they were compensated with €10.

4.6.4.3 Sample

We recruited a total of 60 participants who provided their informed consent prior to the commencement of the study. They had either normal or corrected vision and confirmed their overall well-being. The participants were randomly assigned to the control group, the farm ambiance priming group, or the VR technology priming group. Before conducting the subsequent analyses, we excluded participants with the most extreme scores on the gamma factor scale of socially desirable response behavior (Kemper et al. 2012). This resulted in a final sample of 57 participants ($N_{G1}=19$, $N_{G2}=18$, $N_{G3}=20$, $M_{age}=24.58$, $SD_{age}=8.75$, 57.9% male). Of these participants, 27 indicated they had never previously participated in a farm tour, while 33 reported having no prior experience with the use of VR headsets, 14 had a little experience, 8 had moderate experience, 1 had a lot, and 1 had very much experience. Table 1 [hier: Tabelle 28] presents an overview of descriptive statistics for the three groups, displaying the variables from the conceptual framework as well as the control variables.

Variable	Group 1 (Priming: Farm ambiance, N=19)		Group 2 (Priming: VR technology, N=18)		Group 3 (Control, N=20)	
	M	SD	M	SD	M	SD
SPES-SL	3.20	1.15	3.79	.65	3.25	1.07
SPES-PA	2.61	1.01	3.10	.95	2.39	.92
Perceived Enjoyment	4.11	.94	4.17	.71	4.15	.81
Recommendation Intention	7.16	2.41	6.44	2.50	5.60	2.85
Attitude Toward the Retailer	5.33	1.38	5.98	.75	6.05	1.04
Prior experience with VR headsets	1.63	1.01	1.50	.79	1.80	.95
Prior experience with farm tours	.53	.51	.56	.51	.35	.49
SUIS	3.91	.94	3.80	.81	3.58	.86
Age	24.05	8.20	23.44	7.33	26.10	10.49

Tabelle 28: Descriptive statistics

Notes: M=Mean, SD=Standard deviation

4.6.5 Results

4.6.5.1 Preliminary considerations

The hypotheses were tested via partial least squares structural equation modeling (PLS-SEM) in R (version 4.3.2) using the *sempr* package (version 2.3.2). We decided to use PLS-SEM because it is the recommended approach for analyzing experimental designs in structural equation models (Bagozzi, Yi, and Singh 1991). Following the approach of Hair et al. (2019), we first assess the suitability of our sample size. We then proceed to assess the measurement model and structural model. To determine the minimum sample size for a given significance level and desired statistical power, we use the inverse square root method developed by Kock and Hadaya (2018). The analysis of our main model yields a minimum significant path coefficient of .327 (see Table 4 [hier: Tabelle 31]). With a significance level of .05 and a power of .8, the minimum sample size is given by:

$$n_{min} > \left(\frac{2.486}{.327} \right)^2 \cong 58$$

Given that the inverse square root method is rather conservative, in that it slightly overestimates the sample size required to render an effect significant at a given power level (Hair et al. 2021), we conclude that our sample size of $N=57$ is adequate for the analysis.

4.6.5.2 Measurement model assessment

The first step in evaluating reflective measurement models in PLS-SEM is to examine indicator loadings (Hair et al. 2019). Indicator loadings greater than .708 are recommended, as they indicate that the construct explains more than 50 percent of the indicator's variance (Hair et al. 2019). Table 2 [hier: Tabelle 29] shows that this recommendation is met for all multi-item reflective constructs. The second step in reflective measurement model assessment involves examining internal consistency reliability, which is the extent to which indicators measuring the same construct are associated with each other (Hair et al. 2019; 2021). The most commonly used metrics in PLS-SEM are composite reliability ρ_c and Cronbach's alpha (Hair et al. 2021). We use Cronbach's alpha because it is the more conservative measure (Hair et al. 2021). Table 2 [hier: Tabelle 29] shows that all Cronbach's alpha values exceed the recommended threshold of .700 (Nunnally 1978; Hair et al. 2021). The third step is to assess convergent validity, which is the extent to which the construct converges in order to explain the variance of its indicators (Hair et al. 2021). The most

commonly used metric to assess convergent validity is the average variance extracted (AVE). Table 2 [hier: Tabelle 29] shows that all AVE meet the .500 cutoff required (Fornell and Larcker 1981; Hair et al. 2021). The fourth step is to assess discriminant validity, which is the extent to which a construct is empirically distinct from other constructs in the structural model (Hair et al. 2021). The most commonly used metrics in PLS-SEM are the Fornell-Larcker criterion (Fornell and Larcker 1981) and the heterotrait-monotrait ratio (HTMT) of correlations (Henseler et al. 2015). Table 3 [hier: Tabelle 30] shows that the square roots of the AVE exceed the interconstruct correlations, indicating discriminant validity according to the Fornell-Larcker criterion (Fornell and Larcker 1981). Furthermore, our results also indicate discriminant validity according to the HTMT criterion, given there are no HTMT values above .850 (Hair et al. 2021). In line with Sarstedt et al. (2019), we do not consider discriminant validity between the higher order construct SPES and its lower order dimensions SPES-SL and SPES-PA, as a violation of discriminant validity between these constructs is expected.

Construct	Items	IL	CA	AVE
SPES-SL	I felt like I was actually there in the environment of the virtual farm tour.	.878	.838	.674
	It seemed as though I actually took part in the action of the virtual farm tour.	.791		
	It was as though my true location had shifted into the environment in the virtual farm tour.	.810		
	I felt as though I was physically present in the environment of the virtual farm tour.	.802		
SPES-PA	The objects in the virtual farm tour gave me the feeling that I could do things with them.	.779	.799	.622
	I had the impression that I could be active in the environment of the virtual farm tour.	.763		
	I felt like I could move around among the objects in the virtual farm tour.	.782		
	It seemed to me that I could do whatever I wanted in the environment of the virtual farm tour.	.828		
SPES	SPES-SL	.936	.835	.858
	SPES-PA	.916		
Perceived Enjoyment	How much did you enjoy the virtual farm tour?	n/a	n/a	n/a
Recommendation Intention	How likely is it that you would recommend the virtual farm tour to a friend or colleague?	n/a	n/a	n/a
Attitude Toward the Retailer	bad – good	.922	.878	.805
	negative – positive	.952		
	unpleasant – pleasant	.811		

Tabelle 29: Measurement items

Notes: IL=Indicator Loading, CA=Cronbach's Alpha, AVE=Average Variance Extracted

#	Construct	AVE	Correlations/Square Roots of AVE					
			1	2	3	4	5	6
1	SPES-SL	.674	.821					
2	SPES-PA	.622	.716	.788				
3	SPES	.858	-	-	.926			
4	Perceived Enjoyment	n/a	.508	.398	.493	n/a		
5	Recommendation Intention	n/a	.419	.485	.486	.408	n/a	
6	Attitude Toward the Retailer	.878	.315	.197	.281	.382	.348	.897

Tabelle 30: Fornell-Larcker criterion

Notes: AVE=Average Variance Extracted

4.6.5.3 Structural model assessment

Prior to the evaluation of the structural model, we calculated the variance inflation factors (VIF) for all predictor constructs. Given there are no VIF values above 5, we conclude that multicollinearity does not pose a problem in this study.

To examine the impact of audio priming on SPES, the structural model includes two dummy variables, one for each treatment group, with the control group as the reference group. Thus, the corresponding bootstrapped path coefficients represent the differences in SPES means between each treatment group and the control group. In line with Bagozzi, Yi, and Singh (1991), we use γ to denote these coefficients, while using β for the others.

To assess the structural model, we ran a bootstrapping analysis with 10,000 resamples. The results (Table 4 [hier: Tabelle 31], Model 1) show that priming participants on farm ambiance (Group 1) had no significant effect on SPES relative to the control group ($\gamma=.035$, confidence interval_{95%} [-.312, .383], $p>.1$, H_{1a}). However, priming them on VR technology significantly increased SPES ($\gamma=.327$, confidence interval_{95%} [.038, .574], $p<.05$, H_{1b}). With regards to H₂, we find that SPES significantly increased perceived enjoyment ($\beta=.502$, confidence interval_{95%} [.269, .688], $p<.01$, H₂). Regarding H₃ and H₄, the results show that perceived enjoyment significantly increased both recommendation intention ($\beta=.407$, confidence interval_{95%} [.160, .619], $p<.01$, H₃) and attitude toward the retailer ($\beta=.385$, confidence interval_{95%} [.100, .659], $p<.05$, H₄). To account for potential other factors influencing SPES, we control for the participants' prior experience with VR headsets, their prior experience with farm tours, their everyday use of mental imagery (SUIS), and their age. The results (Table 4 [hier: Tabelle 31], Model 2) show that all hypothesized effects remain significant. We found no significant differences in positive or negative affect before and after the intervention between the three groups, as indicated by the PANAS.

Hypothesis	Path	Model 1	Model 2
<i>Hypothesized paths:</i>			
H _{1a}	Group 1 (Priming: Farm ambiance) → SPES	.035 (.177)	.009 (.139)
H _{1b}	Group 2 (Priming: VR technology) → SPES	.327 (.138) **	.299 (.118) **
H ₂	SPES → Perceived Enjoyment	.502 (.110) ***	.497 (.107) ***
H ₃	Perceived Enjoyment → Recommendation Intention	.407 (.118) ***	.407 (.118) ***
H ₄	Perceived Enjoyment → Attitude Toward the Retailer	.385 (.154) **	.385 (.154) **
<i>Control variables:</i>			
-	Prior experience with VR headsets → SPES	-	-.234 (.157)
-	Prior experience with farm tours → SPES	-	-.075 (.122)
-	SUIS → SPES	-	.291 (.134) **
-	Age → SPES	-	.232 (.130) *

Tabelle 31: PLS-SEM results

Notes: $R^2_{SPES}=9.4\%$ (Model 1), $R^2_{SPES}=33.8\%$ (Model 2), $R^2_{\text{Perceived Enjoyment}}=24.3\%$, $R^2_{\text{Recommendation Intention}}=16.7\%$, $R^2_{\text{Attitude Toward the Retailer}}=14.6\%$, * $p<.1$, ** $p<.05$, *** $p<.01$, Bootstrapped path coefficients with standard errors in parentheses

4.6.5.4 Common method bias

Our study design minimizes the likelihood of common method bias (CMB) occurring ex ante by incorporating multiple temporal and methodological separations throughout the data collection process (i.e., pre-questionnaire, audio stimuli, virtual farm tour, post-questionnaire) (Podsakoff et al. 2012; Viswanathan and Kayande 2012). To evaluate the potential threat of CMB ex post, we applied Harman's single-factor test, the most widely used technique for detecting CMB in business research (Kock et al. 2021). According to this test, CMB is indicated when an unrotated exploratory factor analysis reveals a single factor that accounts for more than 50% of the variance (Kock et al. 2021). In our study, the first factor accounted for only 28.8% of the variance, indicating no statistical evidence of CMB.

4.6.6 Discussion and implications

The purpose of this study was to determine whether audio priming can enhance consumers' spatial presence and whether spatial presence subsequently increases their perceived enjoyment during

VR experiences, which then translates into key pre-economic variables relevant to retailers. Therein, our research provides valuable insights for both researchers and practitioners.

4.6.6.1 Theoretical implications

Currently, leading retailers are considering how to adapt their strategies to compete in the virtual future (Peukert et al. 2019; Yoo et al. 2023). It is likely that VR headsets will be the preferred way to experience virtual worlds, as 3D interactions are more intuitive to consumers than 2D ones (Ball 2022; Hennig-Thurau et al. 2022). Given the importance of spatial presence in improving VR experiences across various research domains (e.g., Blascovich et al. 2002; Heeter 1992; Jin 2010; Hartmann et al. 2016; Markowitz et al. 2018; Slater and Wilbur 1997), approaches that increase spatial presence are of great interest to retailers. Previous research suggests that consumers who experience a greater spatial presence in virtual retail stores choose a larger variety of products and are less price-sensitive (Meißner et al. 2020). Furthermore, prior studies on VR have associated higher media richness with an improved shopping experience and increased purchase intentions (Moes and van Vliet 2017). Extending these findings, our results show that audio priming can be a simple and cost-effective approach to significantly increase consumers' spatial presence during VR experiences. The increased spatial presence results in greater perceived enjoyment, which ultimately leads to an increased recommendation intention and attitude toward the retailer. Consequently, we advocate the integration of audio priming in various VR applications, such as video games or simulations, but also particularly in retail for virtual tours in physical or virtual stores. We specifically recommend employing audio priming to acquaint consumers with the technology underlying the VR experience. Processing the virtual environment may be challenging, especially for first-time users but also for those with prior experience, potentially leading to a technology shock that reduces spatial presence. Technology priming mitigates this issue by providing consumers with an explanation of what to expect and familiarizing them with the technological aspects of the VR experience, such as the mechanics behind a 360-degree video. We propose that this approach enhances processing fluency by increasing consumers' awareness of the technological aspects of the virtual environment. By understanding the underlying VR technology, consumers are able to anticipate the experience more accurately, making it easier to process, which leads to a more positive response due to the familiarity it creates (Reber, Schwarz, and Winkielmann 2004) and subsequently an elevated spatial presence (Cerda et al. 2021; Sjölie 2012). Conversely, priming consumers on the content's context, such as farm ambiance in our study, does

not increase spatial presence and is thus not recommended. A possible general explanation is that contextual priming triggers associations related to the specific situational context, which can either align with or contradict the priming. Specifically, we argue that farm ambiance priming is ineffective because it creates a mental image that conflicts with some participants' pre-existing, often idealized notions of what a farm should be (Christoph-Schulz et al. 2018). In contrast, technology priming is independent of the situational context and does not rely on pre-existing associations. In line with fluency theory, a mismatch between pre-existing associations and the actual experience may disrupt processing fluency, making the VR experience feel unfamiliar and, in turn, reducing spatial presence. This reasoning is further supported by expectation-confirmation theory (Oliver 1980). Priming participants on farm ambiance might excessively raise their expectations, allowing extensive scope for imagination that the actual VR experience may fail to meet, ultimately resulting in disappointment.

4.6.6.2 Managerial implications

An illustrative example of the potential of virtual tours in retail is the detailed tracking of a product's journey: from its source through its processing stages to its final placement on a retail shelf. Using this approach, retailers, and also manufacturers, could address the information gaps prevalent in the market and meet consumers' desire for greater transparency, especially regarding ethical practices in the production of animal products (Caracciolo et al. 2016), which could constitute a valuable competitive advantage. As consumers increasingly seek information about the origins of animal products sold by retailers (Boogaard et al. 2011; Vanhonacker et al. 2008), some grocery retailers have responded by partnering with farms and actively using visual content, such as videos showcasing their partner farms, as marketing material to promote the sale of animal products and ultimately boost revenue (e.g., EDEKA's BauernLiebe marketing campaign, see Rasting 2021). These videos offer consumers a glimpse into farm operations, but virtual farm tours can take this a step further. Positioned between traditional video formats and in-person farm tours, virtual farm tours offer a unique combination of convenience and presence, delivering the advantages of both mediums (Schütz, Kurz, and Busch 2022). In fact, even virtual farm tours have already been implemented in practice. For example, a REWE supermarket began offering visual insights into livestock stables via livestreams and VR headsets at the point of sale in 2018 and has continued using them ever since, highlighting their ongoing relevance to consumers (REWE Richrath 2018; Kletschke 2019; Schütz, Kurz, and Busch 2022). Beyond farm partnerships, virtual

tours hold even greater potential as grocery retailers increasingly integrate vertically and expand their in-house production. Many retailers produce key product categories themselves. For instance, Aldi and Lidl operate their own coffee roasteries (Giuri 2018; Sachsenröder 2022). In this regard, in-store virtual tours could be an effective tool for educating customers about sourcing, roasting processes, and quality control measures. By allowing customers to virtually experience these production sites, retailers can reinforce their commitment to transparency, strengthen brand trust, and differentiate their private-label offerings in a competitive market. Additionally, grocery retailers could utilize virtual tours to enrich the shopping experience by offering educational content, such as cooking demonstrations, food preparation tips, or sustainability insights, creating a more interactive and informative shopping process.

Regarding the implementation in retail settings, cost-effective 3 DoF VR headsets seem to be particularly advantageous. Their restricted motion range makes them suitable for novice VR users, providing a simpler user experience compared to headsets that require controllers and offer extensive interaction capabilities. Deploying advanced 6 DoF VR headsets, which require the creation of complex virtual environments, presents a greater challenge and financial burden for retailers. This is because creating intricate virtual worlds and environments requires fixed infrastructure, advanced tracking technology (Rauschnabel et al. 2022), and a heightened level of technical skill to achieve high-quality graphical realism (Pan and Hamilton 2018). Furthermore, prior research has shown that more is not always better when it comes to VR headsets. Specifically, Frank et al. (2024) found that the fidelity, defined as the degree of conformity between the visual quality and experience in VR to the same phenomena in the real world (Huang and Klippel 2020), conveyed by different VR headsets has no general effect on consumers' repatronage intentions in virtual retail stores, leading them to conclude that lower fidelity requirements could expand integration opportunities with the broader range of VR headsets already available on the market.

4.6.7 Limitations and future research

The results and implications of this study should be considered in light of some important limitations. First, in terms of methodology, our study is based on a German convenience sample. Additionally, our sample size of $N=57$ is relatively small. Given the complexity and cost associated with VR headset experiments, such a sample size is common in this field of research, as suggested by a literature review from Xi and Hamari (2021), which includes experimental VR studies with

sample sizes as small as $N=16$. However, this raises questions about reproducibility. Consequently, it is imperative to replicate the findings of this study in various research contexts, across different cultures, with larger and ideally representative samples.

Second, laboratory experiments can fail to capture the complexity of real world settings and may not generalize well to field settings (Levitt and List 2007). Thus, we encourage replicating the findings of this study in more realistic field experiments that take into account, for example, distraction effects that may be present at the point of sale but not in laboratory settings. Moreover, in our laboratory experiment, participants did not have the option to skip the priming. However, in a real world setting, users may prefer to bypass the priming to start the VR experience more quickly. Thus, future research could examine whether the positive impact of audio priming on spatial presence persists when users are given the option to skip the priming at any time or presented with shorter priming stimuli.

Third, the participant demographic in our study predominantly comprised individuals with minimal to no prior experience with VR headsets (33 with none, 14 with a little, 8 with moderate, 1 with a lot, and 1 with very much). Future research would benefit from including a larger proportion of frequent VR users to examine how increased prior VR headset experience impacts the effects observed in our study. While our model accounted for prior VR headset experience as a control variable, indicating that spatial presence tended to be less pronounced among participants with greater VR headset experience, exploring this effect in more evenly distributed samples (e.g., 50% without and 50% with prior VR headset experience) would provide valuable insights into the importance of prior VR headset experience.

Fourth, another interesting avenue for future research is to explore the impact of audio priming on spatial presence using advanced 6 DoF VR headsets. Given the greater immersion provided by 6 DoF VR headsets (Pan and Hamilton 2018; Rauschnabel et al. 2022), audio priming might exert a different influence on spatial presence compared to 3 DoF VR headsets.

Fifth, a further promising avenue for future research is the inclusion of additional constructs related to the farm. Variables such as trust in farming practices, perceived authenticity of the farm, and perceived animal welfare could provide deeper insights into how consumers perceive virtual farm tours. While our study primarily focuses on the implications for grocery retailers, virtual farm tours can influence consumers' perceptions of both the farm and the retailer facilitating the experience.

Some grocery retailers actively position themselves as intermediaries that ensure transparency in sourcing and production practices, showcasing farm partnerships as part of their brand image (e.g., Rasting 2021; REWE Richrath 2018). As such, the distinction between farm-related and retailer-related perceptions may not always be clear-cut. Nevertheless, future research could further explore this differentiation by explicitly measuring farm-related outcomes alongside retailer-related outcomes to assess their relative impact. This could provide a more nuanced understanding of how virtual farm tours shape consumer attitudes toward both the farms and the retailers offering these experiences. Moreover, the absence of such farm-related variables in our model may help explain the observed mean differences in the downstream outcome variables (see Table 1 [hier: Tabelle 28]). For instance, participants in the farm ambiance priming group may have generally had greater trust in farming practices or perceived animal welfare more positively during the virtual farm tour—both of which could plausibly have contributed to a higher recommendation intention.

Sixth, we argue that the effect of audio priming on spatial presence can be explained by fluency theory: Audio priming consumers on VR technology increases processing fluency, leading to a more positive response to the stimulus due to the sense of familiarity it creates, ultimately increasing spatial presence (Cerda et al. 2021; Reber, Schwarz, and Winkielman 2004; Sjölie 2012). However, as we did not directly assess processing fluency or the sense of familiarity in our research, we cannot conclusively attribute the observed effect to this explanation. Therefore, alternative explanations remain plausible. Accurately measuring processing fluency and the sense of familiarity in the context of VR presents distinct challenges, highlighting opportunities for further research. One alternative explanation is that the audio priming stimulus has a sensitizing effect, aiding in the development of cognitive processes necessary for establishing spatial presence in VR environments (Wirth et al. 2007). Another explanation could be that the audio priming simply increases consumers' attention and concentration on the upcoming VR experience, thereby facilitating the conditions required for spatial presence (Draper, Kaber, and Usher 1998; Hartmann et al. 2016; Schubert, Friedmann, and Regenbrecht 2001; Wirth et al. 2007).

4.6.8 Appendix

Group 1: Priming (Farm ambiance)

Stand comfortably and relaxed and slowly come to rest. Feel whether you are really standing comfortably. If not, change your posture again. Now, close your eyes and pull the VR headset over

your head with your eyes closed. Now, press the button on the side. Keep your eyes closed. Take a few deep breaths. Concentrate on your breathing and feel how your stomach rises and falls with each breath. Just pay attention to your breath - and to the fact that you are becoming more and more relaxed.

Imagine you have been invited to visit a farm. You are picked up, and when you get there, you are greeted by a farmer. You walk a few steps across the farmyard. You feel the slightly muddy ground under your feet and a pleasantly cool breeze on your skin. You take a deep breath. The fresh air flows through your lungs. You are now standing in front of a barn where pigs are kept. The farmer gives you an information sheet about how the pigs are kept and invites you to explore the barn at your leisure. Now open your eyes and take your time to look around. You can start your tour of the barn at any time by focusing on the barn door.

You are now standing in front of the barn again. Now, close your eyes again. The farm tour is now finished. Keep your eyes closed for a moment and take a few deep breaths. Now, remove the VR headset from your head. Open your eyes when you are ready. Be fully awake again.

Group 2: Priming (VR technology)

Stand comfortably and relaxed and slowly come to rest. Feel whether you are really standing comfortably. If not, change your posture again. Now, close your eyes and pull the VR headset over your head with your eyes closed. Now, press the button on the side. Keep your eyes closed. Take a few deep breaths. Concentrate on your breathing and feel how your stomach rises and falls with each breath. Just pay attention to your breath - and to the fact that you are becoming more and more relaxed.

You are about to experience a 360-degree video. This is a video that provides a view in all directions from the camera's point of view. 360-degree videos are recorded with an omnidirectional camera to provide a sharp and detailed image - regardless of which direction the viewer is facing. For this study, a 360-degree video of a barn where pigs are kept was recorded. You are right in front of this barn. At the beginning, you are shown an information sheet about how the pigs are kept. You can take a look at the barn. Now open your eyes and look around. You can start the tour of the barn at any time by focusing on the barn door.

You are now standing in front of the barn again. Now, close your eyes again. The farm tour is now finished. Keep your eyes closed for a moment and take a few deep breaths. Now, remove the VR headset from your head. Open your eyes when you are ready. Be fully awake again.

Group 3: Control

You stand in the center of the room and have enough space around you. Take a position in which you want to spend the next few minutes. Now, pull the VR headset over your head. Now, press the button on the side and look around. You can start the barn tour at any time by focusing on the barn door.

The VR experience has now concluded. You can remove the VR headset from your head.

5 Zusammenfassung, Implikationen und Limitationen

5.1 Zusammenfassung der Ergebnisse

Zur Beantwortung der **ersten Forschungsfrage** „*Wie lässt sich Kundenwechselverhalten im Dienstleistungskontext definieren und von verwandten Konzepten abgrenzen?*“ wurde der Begriff Kundenwechselverhalten im Dienstleistungskontext in Kapitel 2.1.2 als „das Phänomen, dass sich ein Kunde bei der Auswahl aus mehreren Dienstleistungen für eine andere als die bisher genutzte entscheidet (Keaveney, 1995)“, definiert und vom Begriff der Kundenabwanderung abgegrenzt. Dabei wurde herausgestellt, dass Kundenwechselverhalten stets eine Kundenabwanderung voraussetzt und daher als übergeordneter Begriff zu verstehen ist. Darüber hinaus wurde in Kapitel 2.4 der Zusammenhang zwischen Kundenwechselverhalten und Kundenloyalität aufgezeigt, um die Notwendigkeit einer eigenständigen theoretischen Auseinandersetzung mit dem Kundenwechselverhalten zu begründen.

Zur Beantwortung der **zweiten Forschungsfrage** „*Welche theoretischen Ansätze eignen sich zur Erklärung des Kundenwechselverhaltens im Dienstleistungskontext?*“ wurden, aufbauend auf dem Literaturüberblick zu Kundenwechselverhalten im Dienstleistungskontext von Chuang und Tai (2016), die vier in der Phase der Modellformulierung entwickelten theoretischen Ansätze zur Erklärung von Kundenwechselverhalten in Kapitel 2.4 dargestellt und miteinander verglichen. Dabei zeigte sich zunächst, dass das PPM-Modell in der Literatur am häufigsten Anwendung findet, was als Indiz für seine Relevanz gewertet werden kann. Darüber hinaus wurde argumentiert, dass es aufgrund seines eindeutigen intendierten Anwendungsbereichs sowie seiner aus der Migrationsforschung übernommenen theoretischen Fundierung am besten geeignet ist, Kundenwechselverhalten im Dienstleistungskontext zu erklären.

Zur Beantwortung der **dritten Forschungsfrage** „*Was sind die Determinanten des Kundenwechselverhaltens im digitalen Dienstleistungskontext?*“ lieferten die Beiträge 1 und 2 zunächst meta-analytische Evidenz zum PPM-Modell im allgemeinen Dienstleistungskontext, indem sie erstmals eine umfassende Übersicht über dessen Anwendung in der bisherigen Forschung bereitstellten und die Effekte zentraler Prädiktoren auf das Kundenwechselverhalten meta-analytisch untersuchten. Auf Basis von 148 empirisch-quantitativen Studien wurde analysiert, welche Variablen in der bisherigen Forschung am häufigsten zur Erklärung des

Kundenwechselerhaltens im Dienstleistungskontext herangezogen wurden, wie diese jeweils als Push-, Pull- und Mooring-Variablen kategorisiert und mithilfe welcher Messinstrumente sie operationalisiert wurden. Die meta-analytische Strukturgleichungsmodellierung zeigte darüber hinaus, dass ein Modell aus den drei am häufigsten genutzten und eindeutig kategorisierbaren Variablen – Unzufriedenheit (Push), Attraktivität der Alternative (Pull) und Wechselkosten (Mooring) – 30 % der Varianz der Wechselintention und 31 % der Varianz des tatsächlichen Wechselverhaltens erklären kann. Im Ausblick für weitere Forschung hebt Beitrag 2 die Notwendigkeit hervor, die Vergleichbarkeit von PPM-Modell-Studien zu verbessern, indem die im Rahmen der Meta-Analyse identifizierten Variablen und Messinstrumente als Referenzpunkt genutzt werden. Darüber hinaus wird angeregt, neue unabhängige Variablen einzubeziehen, um die Varianzaufklärung zu erhöhen – insbesondere kontextspezifische Faktoren sowie bislang kaum untersuchte affektive Variablen. Schließlich wird auf die Bedeutung weiterer Studien zu tatsächlichem Wechselverhalten und bislang nicht erforschten Kontexten verwiesen.

Auf diesen Forschungsaufrufen aufbauend gingen die Beiträge 3 bis 6 explizit auf die Determinanten des Kundenwechselerhaltens im Kontext digitaler Dienstleistungen ein. Dabei wurden die in Kapitel 2.3 herausgearbeiteten spezifischen Besonderheiten digitaler Dienstleistungen berücksichtigt, die das Kundenwechselerhalten beeinflussen: Aufgrund der aus der spezifischen Kostenstruktur digitaler Dienstleistungen resultierenden weiten Verbreitung indirekter Erlösmodelle verliert einerseits der Preis als zentrale Wechselbarriere an Bedeutung und andererseits wird eine parallele Nutzung mehrerer Angebote erleichtert, wodurch das in Kapitel 2.1.2 beschriebene teilweise Kundenwechselerhalten an Bedeutung gewinnt (Clement et al., 2019; Pick, 2016; Urbach, 2016; Ye & Potter, 2011). Zugleich machen positive Feedback-Effekte, Systemwettbewerb, Netzwerkeffekte und datenbasierte Nutzungspfadabhängigkeiten Kundenwechselerhalten jedoch tendenziell unattraktiver und führen zu einer hohen Marktkonzentration, die die tatsächliche Verfügbarkeit von Alternativen einschränkt (Clement et al., 2019; Urbach, 2016). Unter solchen Bedingungen gewinnen im Rahmen des PPM-Modells vor allem Mooring-Variablen an Bedeutung, während Push- und Pull-Faktoren ihre Wirkung insbesondere dann entfalten können, wenn realistische Alternativen vorhanden sind.

Der Beitrag 3 untersuchte vor diesem Hintergrund die Determinanten der Wechselintention sowie des tatsächlichen Wechselverhaltens von Internetnutzern von herkömmlichen Suchmaschinen zu ökologisch nachhaltigen Suchmaschinen. Die Ergebnisse zeigen, dass der Pull-Faktor – bestehend

aus Attraktivität der Alternative, subjektiver Norm, wahrgenommener Nützlichkeit und wahrgenommenen ökologischen Vorteilen – die Wechselintention deutlich erhöht. Der Mooring-Faktor – bestehend aus Wechselkosten, Trägheit und geringem Bewusstsein für nachhaltigen Konsum – reduziert die Wechselintention hingegen stark und schwächt zugleich sowohl den Einfluss des Pull-Faktors als auch den Zusammenhang zwischen Wechselintention und tatsächlichem Verhalten. Der Push-Faktor – bestehend aus wahrgenommener Umweltbedrohung und schlechter Servicequalität – übt keinen Effekt aus. Die Wechselintention wirkt sich positiv auf das tatsächliche Wechselverhalten aus.

Der Beitrag 4 untersuchte die Determinanten der Wechselintention sowie des tatsächlichen Wechselverhaltens von Kunden von Chatbots zu menschlichen Kundenservice-Mitarbeitern. Die Ergebnisse verdeutlichen, dass der Pull-Faktor, der vor allem durch die wahrgenommene Nützlichkeit menschlicher Servicemitarbeiter bestimmt wird, die Wechselintention erhöht. Demgegenüber hemmt der Mooring-Faktor, der in erster Linie auf Trägheit zurückzuführen ist, die Wechselintention. Unerwartet zeigt sich zudem, dass der Push-Faktor – geprägt von Unzufriedenheit und wahrgenommener Ineffizienz des Chatbots – die Wechselintention reduziert, was darauf hindeutet, dass Kunden sich bei negativen Chatbot-Erfahrungen eher vollständig vom Kundenservice abwenden, anstatt auf menschliche Unterstützung zurückzugreifen. Darüber hinaus erweist sich die wahrgenommene Schwierigkeit der Aufgabe als zentrale Antezedenz, da sie Push- und Pull-Faktoren verstärkt, während sie den Mooring-Faktor abschwächt. Auch in diesem Beitrag bestätigt sich ein positiver Zusammenhang zwischen Wechselintention und tatsächlichem Wechselverhalten.

Vor dem Hintergrund der in den Beiträgen 3 und 4 aufgezeigten hohen Relevanz des Mooring-Faktors, insbesondere getrieben durch die Variable Trägheit, untersuchte Beitrag 5 auf Basis der Status-quo-Bias-Theorie und der Customer-Inertia-Marketing-Theorie die Antezedenzen einer Trägheitsmentalität, um zu verstehen, wodurch diese beeinflusst werden kann. Die Ergebnisse zeigen, dass die Minimierung von Denken und Bedauern zentrale psychologische Antezedenzen einer Trägheitsmentalität darstellen, die wiederum durch die Konsistenz und das Ausmaß des bisherigen Konsums geprägt werden. In Übereinstimmung mit den Ergebnissen aus den Beiträgen 3 und 4 weist die Trägheitsmentalität einen negativen Einfluss auf die Abwanderungsintention auf. Zudem dämpft sie den negativen Effekt von Servicefehlern auf die Abwanderungsintention ab, was die zentrale Bedeutung der Variable Trägheit zusätzlich hervorhebt.

In Anbetracht der bislang geringen Berücksichtigung affektiver Variablen im PPM-Modell untersuchte Beitrag 6 bewusst den Einfluss des wahrgenommenen Vergnügens als affektive Pull-Variable. Zur gezielten Hervorrufung von Emotionen wurde der Kontext einer virtuellen Stallbesichtigung gewählt, da virtuelle Realitäten durch ihre kontrollierten und immersiven Umgebungen besonders gut geeignet sind, affektive Reaktionen zu erzeugen (Somarathna et al., 2023). Anders als in klassischen PPM-Studien wurde die Wechselintention nicht direkt erhoben, da für Konsumenten in diesem Kontext keine eindeutige Entscheidungssituation zwischen zwei Alternativen bestand. Stattdessen fokussierte die Untersuchung auf die Weiterempfehlungsintention sowie die Einstellung gegenüber dem Händler als zentrale Zielgrößen, die Rückschlüsse auf die Akzeptanz der virtuellen Stallbesichtigung und damit indirekt auch auf potenzielle Wechselentscheidungen ermöglichen. Die Ergebnisse zeigen, dass wahrgenommenes Vergnügen einen positiven Einfluss auf beide Zielgrößen hat, was die Relevanz affektiver Variablen für das Verständnis von Kundenwechselerhalten im Rahmen des PPM-Modells unterstreicht.

Zusammenfassend zeigen die Beiträge 3 bis 6, dass Kundenwechselerhalten im digitalen Dienstleistungskontext durch ein Zusammenspiel von Push-, Pull- und Mooring-Faktoren beeinflusst wird. Der Push-Faktor zeigt ein heterogenes Bild. Während in Beitrag 3 kein signifikanter Effekt nachgewiesen werden konnte, ergab sich in Beitrag 4 sogar ein signifikant negativer Effekt. Der Pull-Faktor hat dagegen über alle Beiträge hinweg einen eindeutig positiven Einfluss auf die Wechselintention. Besonders relevant sind dabei die etablierten Variablen Attraktivität der Alternative, wahrgenommene Nützlichkeit und subjektive Norm. Kontextspezifische Variablen wie wahrgenommene Umweltvorteile (Beitrag 3) oder wahrgenommene Anpassungsfähigkeit menschlicher Servicemitarbeiter (Beitrag 4) können ergänzende Beiträge zur Varianzaufklärung leisten, spielen im Vergleich jedoch eine untergeordnete Rolle. Die Einbeziehung bislang im Rahmen des PPM-Modells wenig berücksichtigter affektiver Variablen, wie wahrgenommenes Vergnügen (Beitrag 6), erweist sich zudem als zielführend hinsichtlich einer erhöhten Varianzaufklärung. Der Mooring-Faktor zeigt über alle Studien hinweg einen klar negativen Einfluss auf die Wechselintention, wobei insbesondere die Variable Trägheit relevant ist. Auch hier können kontextspezifische Variablen wie ein geringes Bewusstsein für nachhaltigen Konsum (Beitrag 3) oder Angst vor sozialer Interaktion (Beitrag 4) zusätzliche Varianz erklären.

Insgesamt konnten die drei Forschungsfragen im Rahmen der Dissertation beantwortet werden. Gleichzeitig ergeben sich aus den Ergebnissen zahlreiche theoretische, praktische sowie gesellschaftliche und politische Implikationen²², die in den folgenden Kapiteln diskutiert werden.

5.2 Theoretische Implikationen

Aus den in dieser Arbeit gewonnenen Erkenntnissen ergeben sich zahlreiche theoretische Implikationen, die im Folgenden dargelegt werden.

Wie in den Beiträgen 1 und 2 aufgezeigt, stellen Heterogenität und mangelnde Vergleichbarkeit zwischen PPM-Studien zentrale Herausforderungen dar: Die gewählten unabhängigen Variablen, ihre Kategorisierung, ihre Messung sowie die berichteten Effektgrößen und -richtungen variieren erheblich. Dies ist, wie in Beitrag 2 ausführlich dargestellt, aus mehreren Gründen problematisch. Unter anderem behindert die inkonsistente Konzeptualisierung die **Theoretisierung**. Aufbauend auf den in dieser Dissertation gewonnenen Erkenntnissen wird daher im Folgenden zunächst diskutiert, wie das PPM-Modell zukünftig eindeutig den Charakter einer Theorie erlangen könnte.

Eine **Theorie** wird im Rahmen dieser Arbeit als „eine Menge von Aussagen über die Beziehung(en) zwischen zwei oder mehr Konzepten bzw. Konstrukten“ definiert (Jaccard & Jacoby, 2010, S. 28). Zentrale Elemente sind nach Kuß (2013) Konzepte mit ihren Definitionen, Aussagen über Beziehungen zwischen den Konzepten sowie Argumente, die diese Aussagen begründen. Ergänzend hebt Hunt (2010) als Merkmale hervor, dass Theorien systematische und widerspruchsfreie Beziehungen zwischen ihren Aussagen aufweisen, allgemeine Gesetzmäßigkeiten formulieren und empirisch überprüfbar sein müssen. In seiner derzeitigen Form erfüllt das PPM-Modell das zweite von Hunt (2010) genannte Merkmal nicht, wie in den Beiträgen 1 und 2 verdeutlicht wurde. Die **Formulierung allgemeiner Gesetzmäßigkeiten** ist mit einem PPM-Modell, das je nach Studie auf variierende unabhängige Variablen zurückgreift und für diese jeweils eigene Hypothesen formuliert, nicht gegeben. Zwei Lösungswege erscheinen möglich: entweder eine Reduktion auf wenige, klar definierte Variablen, wie sie in den Meta-Analysen der Beiträge 1 und 2 aus methodischen Gründen umgesetzt wurde, oder eine Bündelung relevanter Variablen zu den drei Konstrukten höherer Ordnung Push, Pull und Mooring, wie in den Beiträgen

²² Die Wahl zur Herleitung theoretischer, praktischer sowie gesellschaftlicher und politischer Implikationen lässt sich anhand der modernen, erweiterten Definition des Marketings begründen (Kapitel 2.2.1), nach der sich Marketing an drei zentrale Interessensgruppen richtet: die akademische Marketingforschung, die betriebliche Praxis sowie die Gesellschaft als Ganzes (Hunt, 2010).

3 und 4 vorgeschlagen. Letzteres stellt die überzeugendere Option dar, da die Offenheit des PPM-Modells für eine Vielzahl von Variablen, wie ausführlich in Beitrag 4 dargelegt, als besondere Stärke interpretiert werden kann. Sie erlaubt es Forschenden, theoretisch relevante Determinanten flexibel zu integrieren, während durch die Aggregation zu Konstrukten höherer Ordnung Probleme wie Multikollinearität reduziert und die Parsimonie des Modells verbessert werden (Sarstedt et al., 2019). Unter Rückgriff auf die migrationsbasierte Logik des Modells bleibt so zugleich Kohärenz gewahrt (Bansal et al., 2005).

Ein weiterer damit verbundener Aspekt betrifft die **Konzeptualisierung der Push-, Pull- und Mooring-Faktoren**. In der Literatur existieren hierzu zwei Vorgehensweisen: eine Konzeptualisierung als reflektiv-reflektive oder reflektiv-formative Konstrukte zweiter Ordnung (Beitrag 2). Wie in den Beiträgen 3 und 4 dargelegt, erscheint der reflektiv-formative Ansatz plausibler. Während in reflektiven Modellen das Konstrukt die Indikatoren verursacht (MacCallum & Browne, 1993), gilt bei formativen Modellen die umgekehrte Logik: Die Indikatoren bedingen das Konstrukt (Jarvis et al., 2003). Push-, Pull- und Mooring-Faktoren sind daher sinnvoll als formative Konstrukte zu konzeptualisieren. So werden Individuen beispielsweise aufgrund von Unzufriedenheit von ihrem aktuellen Anbieter weggedrängt – die Indikatorvariable Unzufriedenheit verursacht somit den Push-Faktor und nicht umgekehrt.

Ein letztes Problem ergibt sich aus der **Definition des Mooring-Faktors**. Dieser wird in der Migrationsforschung als Faktor beschrieben, der persönliche oder soziale Einflüsse umfasst und eine Migration entweder erschweren oder erleichtern kann (Longino, 1992; Moon, 1995). Diese Doppeldeutigkeit verhindert ebenfalls die Formulierung allgemeiner Gesetzmäßigkeiten. Eine Rückbesinnung auf die wörtliche Übersetzung von „Mooring“ als „Vertäuung“ (PONS Langenscheidt GmbH, o. J.) legt hingegen nahe, den Mooring-Faktor ausschließlich als hemmenden Einfluss zu verstehen. Dies entspricht auch der üblichen Konzeptualisierung in PPM-Studien (Beiträge 1 bis 4). Um eine konsistente theoretische Basis zu schaffen, sollte das „Erleichtern“ daher aus der Definition gestrichen werden.

Aus der Umsetzung dieser Anpassungen ergibt sich eine **Version des PPM-Modells, die alle wesentlichen Merkmale einer Theorie erfüllt**. Push-, Pull- und Mooring-Faktoren werden als reflektiv-formative Konstrukte zweiter Ordnung konzeptualisiert, die sich aus relevanten Variablen erster Ordnung zusammensetzen. Der Mooring-Faktor wird so definiert, dass er persönliche und

soziale Einflüsse umfasst, die einen Wechsel erschweren. Somit lassen sich für das PPM-Modell folgende allgemeine Gesetzmäßigkeiten formulieren: (1) Der Push-Faktor wirkt positiv auf die Wechselintention, (2) der Pull-Faktor wirkt positiv auf die Wechselintention, (3) der Mooring-Faktor wirkt negativ auf die Wechselintention, (4) der Mooring-Faktor schwächt den positiven Einfluss des Push-Faktors auf die Wechselintention, (5) der Mooring-Faktor schwächt den positiven Einfluss des Pull-Faktors auf die Wechselintention, (6) die Wechselintention wirkt positiv auf das Wechselverhalten (Beiträge 3 und 4).

Eine weitere theoretische Implikation besteht in der **Erweiterung des PPM-Modells um affektive Variablen**. Dies erscheint insbesondere dann sinnvoll, wenn Konsumenten die Möglichkeit haben, alternative Dienstleistungen zu testen. Wie Beitrag 6 nahelegt, kann wahrgenommenes Vergnügen als affektive Reaktion auf eine Nutzungserfahrung in solchen Situationen einen positiven Einfluss auf die Wechselintention ausüben. Vor diesem Hintergrund könnte die Integration affektiver Variablen (z. B. Ängstlichkeit, Bedauern, affektives Commitment), die über rein kognitive Abwägungen hinausgehen, zur Verbesserung der Varianzaufklärung des PPM-Modells beitragen.

Eine weitere theoretische Implikation besteht in der potenziellen **Weiterentwicklung des PPM-Modells von einem Partial- zu einem Totalmodell**. Während Totalmodelle versuchen, das gesamte Entscheidungsverhalten in seiner Komplexität abzubilden, fokussieren Partialmodelle auf bestimmte Teilaspekte des Entscheidungsverhaltens (Gröppel-Klein & Kroeber-Riel, 2025; Meffert et al., 2024). Darüber hinaus lassen sich Totalmodelle in Strukturmodelle und Prozessmodelle unterteilen (Backhaus & Voeth, 2014; Meffert et al., 2024). Strukturmodelle betrachten alle relevanten Einflussfaktoren des Entscheidungsverhaltens zugleich, wohingegen Prozessmodelle den zeitlichen Ablauf des Entscheidungsverhaltens als Abfolge aufeinanderfolgender Phasen modellieren (Backhaus & Voeth, 2014; Meffert et al., 2024). Das PPM-Modell ist derzeit als Partialmodell zu klassifizieren, weil es ausschließlich ausgewählte, in Anlehnung an die Migrationsforschung abgeleitete Einflussfaktoren des Wechselverhaltens berücksichtigt (Bansal et al., 2005). Nicht berücksichtigt werden beispielsweise Einflussfaktoren wie Framing-Effekte, die Entscheidungsverhalten durch die unterschiedliche Darstellung von Informationen beeinflussen können (Tversky & Kahneman, 1981). Eine Weiterentwicklung des PPM-Modells zu einem Strukturmodell würde erfordern, einen Vollständigkeitsanspruch zu erheben und sämtliche relevanten Einflussfaktoren des Entscheidungsverhaltens zugleich abzubilden (Backhaus & Voeth, 2014). Eine Weiterentwicklung des PPM-Modells zu einem

Prozessmodell würde hingegen erfordern, den Wechselentscheidungsprozess umfassend zu modellieren, indem beispielsweise in Anlehnung an die Prozessphasen einer Kaufentscheidung weitere Phasen wie Problemerkennntnis, Informationssuche und Entscheidungsfolgen sowie Rückkopplungen zwischen diesen Phasen integriert werden (Gröppel-Klein & Kroeber-Riel, 2025). Im Rahmen der Phase der Problemerkennntnis ließen sich im Kontext von Anbieterwechseln beispielsweise unterschiedliche initiale Auslöser differenzieren: So könnte ein Servicefehler des derzeitigen Anbieters als Auslöser dienen, wodurch vermutlich zunächst der Push-Faktor gebildet würde, oder die Wahrnehmung eines attraktiven Angebots eines alternativen Anbieters, wodurch vermutlich zunächst der Pull-Faktor gebildet würde. Obgleich die Entwicklung eines Totalmodells theoretisch wertvoll wäre, ist anzumerken, dass Totalmodelle aufgrund ihrer Komplexität häufig unhandlich und – im Gegensatz zu Partialmodellen – empirisch kaum überprüfbar sind (Gröppel-Klein & Kroeber-Riel, 2025; Meffert et al., 2024).

Über die theoretische Weiterentwicklung des PPM-Modells hinaus ergeben sich weitere Implikationen zur **Integration angrenzender Theorien**. Eine solche Theorie ist die **Theorie des regulatorischen Fokus** nach Higgins (1997), die zwei grundlegende Formen der Selbstregulierung unterscheidet: den Promotionsfokus, unter dem Individuen nach Fortschritt und Gewinn streben, und den Präventionsfokus, unter dem Individuen nach Sicherheit und der Vermeidung von Verlusten streben (Crowe & Higgins, 1997). Unter einem Promotionsfokus wird der Status-quo nicht als neutral, sondern als negativ erlebt, weil das Verharren in der aktuellen Situation dem Erreichen eines positiven Erlebnisses durch Verbesserung im Weg steht, wohingegen der Status-quo unter einem Präventionsfokus als positiv erlebt wird, weil negative Erlebnisse ausbleiben (Higgins, 2014). Der regulatorische Fokus kann durch Sozialisierung prädisponiert sein und sich chronisch verfestigen, zugleich jedoch auch situativ aktiviert werden (Crowe & Higgins, 1997; Higgins, 1997). Zudem variiert der regulatorische Fokus mit dem Alter: Während jüngere Menschen tendenziell einen stärkeren Promotionsfokus zeigen, weisen ältere Menschen eher einen stärkeren Präventionsfokus auf (Heckhausen, 1997; Lockwood et al., 2005). Der Präventionsfokus und – in umgekehrter Kodierung (Beitrag 3) – der Promotionsfokus könnten im Zuge der Integration in das PPM-Modell als Mooring-Variablen konzeptualisiert werden, da sie persönliche Einflüsse darstellen, die einen Wechsel erschweren. Diese Einordnung entspricht der zuvor dargelegten Auffassung des Mooring-Faktors als hemmenden Einfluss, der die Wechselintention unmittelbar negativ beeinflusst und zugleich als Moderator die positiven Einflüsse der Push- und

Pull-Faktoren auf die Wechselintention abschwächt. In der PPM-Literatur haben beispielsweise Liu et al. (2021) den Präventionsfokus und Promotionsfokus bereits als Variablen berücksichtigt und dabei signifikante Moderationseffekte festgestellt. Zwar erfolgte die Integration nicht in der hier vorgeschlagenen Konzeptualisierung als Mooring-Variablen, die Ergebnisse weisen jedoch darauf hin, dass eine solche theoretische Verknüpfung zu einem umfassenderen Verständnis des Kundenwechselverhaltens beitragen kann.

Eine weitere theoretische Anschlussmöglichkeit ergibt sich durch die Integration der **Status-quo-Bias-Theorie** nach Samuelson und Zeckhauser (1988), die beschreibt, dass Individuen in Entscheidungssituationen überproportional häufig – also stärker, als es unter Annahmen rationaler Entscheidungsfindung zu erwarten wäre – den Status-quo gegenüber möglichen Alternativen bevorzugen (Kahneman et al., 1991; Polites & Karahanna, 2012; Samuelson & Zeckhauser, 1988). In der in Kapitel 2.1.2 gegebenen Definition von Kundenwechselverhalten ist inhärent angelegt, dass Kunden in Wechselsituationen stets vor der Entscheidung zwischen einer neuen und der bestehenden Alternative stehen – es existiert also stets ein Status-quo. Daher erscheint die Berücksichtigung der Status-quo-Bias-Theorie für die Erklärung von Kundenwechselverhalten besonders relevant. Als Manifestation des Status-quo-Bias hat sich in der Literatur die Variable Trägheit etabliert (Polites & Karahanna, 2012). Trägheit kann im Rahmen des PPM-Modells als Mooring-Variable integriert werden (Beiträge 1 bis 4) und weist in PPM-Studien regelmäßig eine hohe relative Bedeutung gegenüber anderen erklärenden Variablen auf (Beiträge 3 und 4), was ihre zentrale Rolle für die Erklärung von Kundenwechselverhalten unterstreicht. Zur Berücksichtigung der Status-quo-Bias-Theorie ist es daher sinnvoll, die Variable Trägheit als festen Bestandteil des Mooring-Faktors in das PPM-Modell aufzunehmen. Eine weitere, damit eng verbundene theoretische Perspektive bietet die **Customer-Inertia-Marketing-Theorie** nach Henderson et al. (2021). Diese Theorie zielt darauf ab, die Antezedenzen von Trägheit zu erklären. Sie positioniert Trägheitsmentalität als zentrale Ursache von Trägheit, die wiederum durch Minimierung des Denkens und Minimierung des Bedauerns beeinflusst wird (Henderson et al., 2021). Diese Variablen werden ihrerseits durch die Konsistenz und das Ausmaß des vorherigen Konsums bestimmt (Henderson et al., 2021). Sofern es in PPM-Studien von Interesse ist, die Ursachen von Trägheit empirisch zu erklären, ist die Integration dieser Theorie sinnvoll.

Schließlich ergibt sich als weitere theoretische Implikation die Möglichkeit, das PPM-Modell in das **Churn-Management** zu integrieren. Derzeit findet das PPM-Modell in der einschlägigen

Literatur keine Berücksichtigung (vgl. z. B. Bruhn, 2022; Pick, 2016). Nach Pick (2016) beginnt das Churn-Management mit der Identifikation von Abwanderungsgründen, wobei eine Unterteilung in kundenbezogene, unternehmensbezogene und wettbewerbsbezogene Gründe vorgenommen wird. Diese Einteilung stellt zwar eine nützliche deskriptive Systematisierung dar, bleibt jedoch theoretisch unpräzise, da sie kein Aussagensystem postuliert. Das PPM-Modell bietet hier einen klaren Mehrwert. Es ordnet die Abwanderungsgründe nicht nur, sondern integriert sie in ein Wirkungsgefüge: Unternehmensbezogene Gründe lassen sich als Push-Variablen interpretieren, die Kunden vom derzeitigen Anbieter wegdrängen, wettbewerbsbezogene Gründe entsprechen Pull-Variablen, die zu einem alternativen Anbieter hinziehen, und kundenbezogene Gründe spiegeln Mooring-Variablen wider, die einen Wechsel hemmen. Damit formuliert das PPM-Modell richtungsweisende Hypothesen über die Wirkung der jeweiligen Faktoren. Zudem weist Pick (2016) darauf hin, dass Forschung und Praxis bislang Schwierigkeiten haben, Interaktionseffekte zwischen verschiedenen Abwanderungsgründen zu identifizieren. Auch hier bietet das PPM-Modell einen Mehrwert, indem es postuliert, dass der Mooring-Faktor die positiven Einflüsse der Push- und Pull-Faktoren abschwächt. Insgesamt bietet das PPM-Modell damit einen theoretisch fundierten Rahmen, um die im Churn-Management bislang nur deskriptiv betrachteten Abwanderungsgründe systematisch zu analysieren.

5.3 Praktische Implikationen

Neben theoretischen Implikationen ergeben sich aus den Erkenntnissen der vorliegenden Arbeit auch zahlreiche praktische Implikationen, die in diesem Kapitel dargelegt werden.

Kundenwechselverhalten umfasst im betriebswirtschaftlichen Kontext von Anbieterwechseln stets zwei Akteure: den Anbieter, der einen Kunden gewinnt, und den Anbieter, der einen Kunden verliert (Beitrag 2). Diese **Dualität** verdeutlicht, dass praktische Implikationen sowohl das Verhindern von Wechseln im bestehenden Kundenstamm – also die **Kundenbindung** – als auch das Auslösen von Wechseln im Kundenstamm der Wettbewerber – also die **Kundenakquisition** – betreffen (Beitrag 2). Entsprechend kann eine Unternehmensstrategie sowohl **offensiv**, durch Maßnahmen zur Akquisition neuer Kunden, als auch **defensiv**, durch Maßnahmen zur Bindung bestehender Kunden, ausgerichtet sein (Fornell, 1992). In der Praxis verfolgen die meisten Unternehmen eine Kombination beider Ansätze (Fornell & Wernerfelt, 1987; 1988).

In den Beiträgen 1 und 2 wurden auf Basis meta-analytischer Evidenz zunächst im allgemeinen Dienstleistungskontext die Variablen **Unzufriedenheit**, **Attraktivität der Alternative** und **Wechselkosten** als die drei am häufigsten verwendeten, wirksamen Push-, Pull- und Mooring-Variablen zur Erklärung von Kundenwechselverhalten identifiziert. Auf dieser Grundlage lassen sich konkrete Handlungsempfehlungen für die betriebliche Praxis ableiten: Im Rahmen einer **defensiven Strategie** zur Bindung des bestehenden Kundenstamms sollten Unternehmen die Zufriedenheit ihrer Kunden sicherstellen, die Attraktivität des eigenen Leistungsangebots aufrechterhalten und Wechselbarrieren errichten (Beitrag 2; Fornell, 1992; Jones et al., 2002). Im Rahmen einer **offensiven Strategie** zur Akquisition neuer Kunden von Wettbewerbern sollten Unternehmen analog dazu darauf abzielen, Unzufriedenheit mit dem Wettbewerbsangebot zu verstärken, die Attraktivität des eigenen Angebots zu betonen und Wechselkosten von Kunden zu kompensieren (Bansal et al., 2005; Beitrag 2). Zwar können Unternehmen die Zufriedenheit der Kunden ihrer Wettbewerber nicht unmittelbar beeinflussen, da diese primär von der jeweiligen Leistungserfüllung durch die Wettbewerber abhängt, jedoch können sie im Sinne des Confirmation-Disconfirmation-Paradigmas die Erwartungen potenzieller Kunden gezielt steuern, indem sie die Schwächen des Wettbewerbsangebots im Vergleich zum eigenen Angebot hervorheben (Beitrag 2; Oliver, 1980). Unabhängig von der gewählten strategischen Ausrichtung sollten Unternehmen darauf abzielen, alle drei identifizierten Maßnahmen im Sinne eines kombinierten Marketingansatzes gleichzeitig einzusetzen (Beitrag 2). Ein wesentlicher Vorteil von Meta-Analysen besteht darin, dass sie empirisch fundierte Verallgemeinerungen ermöglichen (Lütjens et al., 2022). So schlagen beispielsweise Edeling und Himme (2018) basierend auf ihrer Meta-Analyse sowie den Ergebnissen von Edeling und Fischer (2016) in Anlehnung an das Dorfman-Steiner-Theorem (Dorfman & Steiner, 1954) eine konkrete Reallokation des Marketingbudgets anhand der Elastizitäten zwischen verschiedenen Marketingmaßnahmen und der finanziellen Unternehmensleistung vor. Obgleich in den Beiträgen 1 und 2 keine Elastizitäten untersucht wurden und eine entsprechende Ableitung im Sinne des Dorfman-Steiner-Theorems (Dorfman & Steiner, 1954) daher nicht möglich ist, lassen sich auf Grundlage der Pfadkoeffizienten aus der meta-analytischen Strukturgleichungsmodellierung dennoch Hinweise auf die relative Bedeutung einzelner Maßnahmen ableiten. Demnach sollte die Attraktivität des Leistungsangebots höchste Priorität haben, gefolgt von der Kundenzufriedenheit und schließlich den Wechselkosten (Beitrag 2).

Die vertiefenden Anwendungsstudien in den Beiträgen 3 bis 6 bestätigen diese meta-analytische empirische Verallgemeinerung weitgehend, liefern zugleich wertvolle Ergänzungen und weisen auf kontextspezifische Ausnahmen hin. Es zeigte sich zunächst, dass der Pull-Faktor über alle Beiträge hinweg einen eindeutig positiven Einfluss auf die Wechselintention ausübt. Neben der Attraktivität der Alternative erwiesen sich insbesondere die Pull-Variablen **wahrgenommene Nützlichkeit** und **subjektive Norm** als besonders relevant (Beiträge 3 und 4). Anbieter sollten dementsprechend die wahrgenommene Nützlichkeit ihres Angebots gezielt hervorheben und zugleich Bezugspersonen der Kunden, etwa Freunde oder Familienmitglieder, in ihre Marketingmaßnahmen einbeziehen – beispielsweise durch Kommunikationsmaßnahmen, die soziale Einflussfaktoren adressieren und die Entstehung von Markengemeinschaften fördern (Bansal et al., 2005; McAlexander et al., 2002). Eine Analogie zur Migrationsforschung verdeutlicht diesen Mechanismus: Menschen wandern selten allein aus, sondern nehmen enge Bezugspersonen mit (Cooke, 2008). Ähnlich verhält es sich bei Dienstleistungen, wo ein Wechsel häufig im sozialen Umfeld initiiert oder verstärkt wird. Darüber hinaus zeigt Beitrag 6, dass die Berücksichtigung affektiver Variablen, wie etwa der Pull-Variable **wahrgenommenes Vergnügen**, die Varianzaufklärung erhöhen kann. Anbieter sollten daher nicht ausschließlich auf kognitive Leistungsmerkmale fokussieren, sondern auch positive Emotionen gezielt in ihre Angebotsgestaltung und Kommunikation integrieren.

Zudem zeigte sich, dass der Mooring-Faktor durchweg einen negativen Einfluss auf die Wechselintention ausübt. Neben den Wechselkosten erwies sich insbesondere die Variable **Trägheit** als besonders wichtig (Beiträge 3 und 4). Anbieter sollten daher gezielt versuchen, die Trägheit ihrer Kunden zu erfassen und aktiv zu beeinflussen. Einen konkreten Anhaltspunkt dafür liefert Beitrag 5, in dem über eine Wirkungskette psychologischer Antezedenzen gezeigt wurde, dass sich Trägheit aus **der Konsistenz und dem Ausmaß des bisherigen Konsums** entwickelt. Auf dieser Grundlage können Unternehmen ihre Kunden entsprechend segmentieren: Kunden mit geringer Konsistenz und geringem Ausmaß des bisherigen Konsums weisen eine niedrigere Trägheit auf und sind daher stärker gefährdet, abzuwandern oder zu wechseln. Unternehmen sollten ihre begrenzten Ressourcen zur Kundenbindung daher insbesondere auf diese Kundengruppe konzentrieren. Dies gilt insbesondere im Falle von Servicefehlern, weil Trägheit den negativen Einfluss von Servicefehlern auf die Abwanderungsintention abschwächen kann (Beitrag 5). Da Unternehmen in der Regel bereits über die hierfür erforderlichen Daten verfügen (Wedel &

Kannan, 2016), etwa über Nutzungsfrequenz, Vertragslaufzeit oder Interaktionshistorie als Indikatoren für die Konsistenz und das Ausmaß des bisherigen Konsums, handelt es sich dabei um eine einfach umsetzbare Maßnahme mit potenziell hohem Nutzen.

Darüber hinaus erwies sich das **Bewusstsein für nachhaltigen Konsum** als hochrelevante Variable in Nachhaltigkeitskontexten. In Beitrag 3 zeigte sich, dass ein geringes Bewusstsein für ökologisch nachhaltigen Konsum ein höheres absolutes und relatives Bedeutungsgewicht für die Bildung des Mooring-Faktors aufwies als die Variable Trägheit. Kunden mit einem geringen Nachhaltigkeitsbewusstsein sind weniger bereit, von einer nicht-nachhaltigen zu einer nachhaltigen Alternative zu wechseln. Anbieter nachhaltiger Dienstleistungen können diese Erkenntnis beispielsweise nutzen, um im Rahmen der Kundenakquisition gezielt nachhaltigkeitsbewusste Konsumenten anzusprechen, sofern entsprechende Segmentierungsdaten vorliegen, wie dies bereits bei einigen Unternehmen praktiziert wird (Zieseimer et al., 2016).

Im Hinblick auf den Push-Faktor zeigten sich unerwartete Ergebnisse. Während der Push-Faktor in Beitrag 3 keinen signifikanten Einfluss auf die Wechselintention ausübte, zeigte sich in Beitrag 4 ein signifikant negativer Effekt. Dieser wurde dahingehend interpretiert, dass der Push-Faktor nicht zu einem Wechsel von dem Chatbot zu einem menschlichen Kundenservicemitarbeiter führt, wie es bei einem positiven Effekt der Fall wäre, sondern stattdessen zum vollständigen Abbruch der Serviceinteraktion. Neben Unzufriedenheit erwiesen sich dabei **Misstrauen** und **wahrgenommene Ineffizienz des Chatbots** als relevante Variablen zur Bildung des Push-Faktors. Eine mögliche Erklärung für den negativen Effekt ist, dass Kunden nach einer nicht zufriedenstellenden Chatbot-Interaktion frustriert sind und den zusätzlichen Aufwand oder die Wartezeit, die mit dem Wechsel zu einem menschlichen Servicemitarbeiter verbunden sein könnten, nicht mehr auf sich nehmen möchten. Für die betriebliche Praxis bedeutet dies, dass Unternehmen Abbrüche gezielt vermeiden sollten, indem sie den Übergang von Chatbots zu menschlichen Servicemitarbeitern proaktiv, einfach und transparent gestalten. In Beitrag 4 zeigte sich darüber hinaus, dass die **wahrgenommene Schwierigkeit der Aufgabe** eine hochrelevante Antezedenz aller drei PPM-Faktoren darstellt. Besonders hilfreich kann daher eine Einschätzung der Aufgabenschwierigkeit sein: Wenn Kunden zu Beginn einer Anfrage die wahrgenommene Schwierigkeit ihres Anliegens angeben oder der Chatbot diese während der Interaktion automatisch erkennt, können schwierige Fälle frühzeitig an menschliche Servicemitarbeiter weitergeleitet

werden. Auf diese Weise lässt sich Frustration vermeiden und sicherstellen, dass anspruchsvolle Serviceanliegen zufriedenstellend gelöst werden.

5.4 Gesellschaftliche und politische Implikationen

Die Erkenntnisse der vorliegenden Arbeit lassen sich über die betriebliche Ebene hinaus auch auf gesellschaftliche und politische Fragestellungen übertragen.

Gesellschaftlich wünschenswerte Transformationsprozesse können im Kern als umfassende Wechselprozesse von einem Status-quo zu einem Desiderat verstanden werden (Linnér & Wiebeck, 2020; Wiek & Iwaniec, 2014; Wissenschaftlicher Beirat der Bundesregierung Globale Umweltveränderungen, 2011). Vor diesem Hintergrund erscheinen die in dieser Arbeit gewonnenen Erkenntnisse relevant, da sie grundlegende Mechanismen des Wechselverhaltens zwischen Alternativen erklären können.

Der Beitrag 3 untersuchte die Determinanten des Wechselverhaltens von Internetnutzern von herkömmlichen zu ökologisch nachhaltigen Suchmaschinen. Im Folgenden wird – in Annahme einer möglichen Verallgemeinerung über den spezifischen Forschungskontext hinaus – diskutiert, inwiefern sich die Ergebnisse im Kontext der **Nachhaltigkeitstransformation** einordnen lassen, also des gesellschaftlichen Ziels, Leben, Wirtschaften, Produktion und Konsum nachhaltiger zu gestalten, das eine der größten Herausforderungen des 21. Jahrhunderts darstellt (Reisch & Schmidt, 2021; United Nations, 2015).

Die Befunde zeigen, dass Wechselverhalten im Kontext ökologisch nachhaltiger Dienstleistungen nicht durch Push-Faktoren, sondern durch ein Zusammenspiel von Pull- und Mooring-Faktoren bestimmt wird, wobei der Pull-Faktor den stärksten direkten Einfluss auf die Wechselintention ausübt. Die fehlende Relevanz des Push-Faktors lässt sich darauf zurückführen, dass die Status-quo-Alternative von den Konsumenten als funktional und unproblematisch wahrgenommen wird. Wechselbereitschaft entsteht somit vor allem durch den Pull-Faktor, bestehend aus Attraktivität der Alternative, wahrgenommener Nützlichkeit, subjektiver Norm und wahrgenommenen Umweltvorteilen. Für eine **effektive Verbraucherkommunikation** als befähigendes Instrument der Verbraucherpolitik (Sachverständigenrat für Verbraucherfragen, 2024) bedeutet dies, dass Kommunikationsstrategien die positiven Eigenschaften nachhaltiger Alternativen betonen sollten, anstatt die negativen Auswirkungen bestehender Angebote hervorzuheben. Botschaften, die

Vorteile wie geringere CO₂-Emissionen oder verbesserte Luftqualität in den Vordergrund stellen, dürften gemäß den Befunden eine höhere Wirkung zeigen als Ansätze, die auf Defizite der Statusquo-Alternativen verweisen. Mit Blick auf die Framing-Literatur lassen sich diese Kommunikationsstrategien weiter präzisieren. Die Betonung positiver Eigenschaften nachhaltiger Alternativen entspricht einem Gain-Frame, der die Entscheidung für nachhaltige Alternativen als Gewinn gegenüber dem Referenzpunkt positioniert (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Innerhalb eines Gain-Frames haben Konsumenten risikoaverse Präferenzen, wodurch Botschaften, die einen sicheren Vorteil kommunizieren, wirksamer sind als solche, die einen unsicheren, potenziell größeren Vorteil in Aussicht stellen (Tversky & Kahneman, 1981).

Darüber hinaus unterstreichen die Ergebnisse die besondere Bedeutung des Mooring-Faktors, bestehend aus Wechselkosten, Trägheit und geringem Bewusstsein für nachhaltigen Konsum. Der Mooring-Faktor wirkt in Beitrag 3 nicht nur direkt negativ auf die Wechselintention, sondern schwächt zugleich den positiven Einfluss des Pull-Faktors auf die Wechselintention sowie den Zusammenhang zwischen Intention und tatsächlichem Verhalten. Damit kommt ihm eine zentrale Rolle für die Gestaltung der Nachhaltigkeitstransformation zu. Aus verbraucherpolitischer Perspektive können **Wechselkosten** und **Trägheit** gut durch **ökonomische Instrumente** adressiert werden – etwa durch Steuern, Abgaben oder Subventionen, wie sie beispielsweise im Rahmen des Umweltbonus für den Kauf von Elektrofahrzeugen bereits Anwendung fanden (Sachverständigenrat für Verbraucherfragen, 2021). Ein geringes Bewusstsein für nachhaltigen Konsum – konkret in Bezug auf die ökologische Nachhaltigkeitsdimension – wies im Rahmen von Beitrag 3 das höchste relative Bedeutungsgewicht zur Bildung des Mooring-Faktors auf. Dieser Befund verdeutlicht die Notwendigkeit, das **Bewusstsein für nachhaltigen Konsum** in der Bevölkerung gezielt zu stärken, wie es in der Verbraucherforschung bereits gefordert wird (Sachverständigenrat für Verbraucherfragen, 2021).

Darüber hinaus lassen sich die Erkenntnisse der vorliegenden Arbeit auch vor dem Hintergrund der **digitalen Transformation** betrachten. Die Mehrheit der deutschen Bevölkerung betrachtet die digitale Transformation als Chance und würde gerne mehr digitale Technologien im Alltag nutzen (Bitkom e. V., 2025). Aus politischer Perspektive ergibt sich daraus die Implikation, aktiv zum Gelingen dieser Transformation beizutragen. Der Wechsel von analogen zu digitalen Angeboten – etwa beim Online-Banking per App statt am Schalter – lässt sich im Sinne der in Kapitel 2.1.2 beschriebenen Typologie als **Technologiewechsel** einordnen. Die Ergebnisse der meta-

analytischen Moderationsanalyse aus Beitrag 2 zeigen, dass bei Technologiewechseln im Vergleich zu Anbieterwechseln der Pull-Variable Attraktivität der Alternative eine besonders hohe Bedeutung zukommt. Daraus lässt sich ableiten, dass eine effektive Verbraucherkommunikation, die wünschenswertes Wechselverhalten im Kontext der digitalen Transformation fördern soll, insbesondere die Vorteile und positiven Eigenschaften digitaler Alternativen betonen sollte. Analog zu den vorherigen Ausführungen zur Framing-Literatur im Kontext der Nachhaltigkeitstransformation entspricht auch hier die Betonung der positiven Eigenschaften digitaler Alternativen einem Gain-Frame, wodurch die Kommunikation sicherer Vorteile wirksamer ist als die Kommunikation unsicherer, potenziell größerer Vorteile (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Entsprechende Vorteile können beispielsweise durch die gezielte Vermittlung von geringeren Kosten, Nutzerfreundlichkeit, Zeitersparnis oder Komfort hervorgehoben werden. Gleichzeitig sollten jedoch auch der Push-Faktor und der Mooring-Faktor berücksichtigt werden. So stellt mangelnde Digitalkompetenz eine zentrale Mooring-Variable dar (Bitkom e. V., 2025), die – neben anderen Mooring-Variablen wie Wechselkosten, Trägheit und Gewohnheit – gezielt adressiert werden sollte. Im Hinblick auf den Push-Faktor kann es zudem wirksam sein, die Unzufriedenheit mit analogen Angeboten in der Verbraucherkommunikation aufzugreifen, etwa durch die Betonung typischer Nachteile analoger Angebote wie langer Wartezeiten am Schalter.

Darüber hinaus verdeutlichen die empirischen Ergebnisse über die Beiträge hinweg die zentrale Bedeutung des Mooring-Faktors – insbesondere der Variablen Wechselkosten und Trägheit – für die Einschränkung von Wechselverhalten im digitalen Dienstleistungskontext. Zudem wurde in Kapitel 2.3.3 gezeigt, dass Wechselverhalten in digitalen Märkten aufgrund der betriebswirtschaftlichen Besonderheiten digitaler Dienstleistungen – positiver Feedback-Effekte, Systemwettbewerbe, Netzwerkeffekte und datenbasierter Nutzungspfadabhängigkeiten – strukturell erschwert wird. Zusammengenommen können diese Mechanismen Wechselverhalten erheblich hemmen und damit zur Verfestigung von Marktmacht sowie zu einer reduzierten Wettbewerbsdynamik beitragen (Clement et al., 2019; Shapiro & Varian, 1998; Urbach, 2016). Aus politischer Perspektive ergibt sich daraus die Notwendigkeit, **Wechselbarrieren in digitalen Märkten** gezielt abzubauen. Die Europäische Union adressiert dies bereits im Rahmen des Digital Markets Act, einem regulatorischen Instrument, das große digitale Plattformunternehmen, sogenannte Gatekeeper, unter anderem dazu verpflichtet, Nutzern freie Wahlmöglichkeiten bei

zentralen Anwendungen anzubieten (European Commission, o. J.). So muss Apple seit Inkrafttreten der Verordnung in der Europäischen Union etwa die Auswahl des Standard-Browsers freigeben, anstatt Safari automatisch als Standard festzulegen – eine Maßnahme, die bereits Wirkung zeigt, wie die gestiegenen Nutzerzahlen alternativer Webbrowser nach Inkrafttreten des Digital Markets Act belegen (Mukherjee & Chee, 2024; Schieb, 2024).

5.5 Limitationen und Potenziale für zukünftige Forschung

Die in dieser Dissertation behandelten Forschungsfragen konnten auf Basis der durchgeführten empirischen Studien beantwortet werden. Gleichwohl unterliegen die gewonnenen Erkenntnisse bestimmten Limitationen. Eine sorgfältige Auseinandersetzung mit diesen Limitationen ist notwendig, um die Befunde kritisch zu reflektieren und daraus Potenziale für zukünftige Forschung abzuleiten. Im Folgenden werden daher die **Limitationen** der Arbeit sowie daraus resultierende **Forschungsbedarfe** dargelegt, differenziert nach **methodischen** und **inhaltlichen Aspekten**.

Aus methodischer Sicht besteht eine Limitation darin, dass die in den Beiträgen 3 bis 6 durch Primärdatenerhebungen gewonnenen Erkenntnisse ausschließlich auf **Selbsteinschätzungen der Teilnehmer** im Rahmen von **Befragungsstudien** beruhen. Damit gehen eine Reihe von potenziellen Verzerrungen einher (Asdecker & Karl, 2023). Dazu zählen insbesondere die **Methodenverzerrung** (engl. method bias), die entsteht, wenn Teilnehmer aufgrund von mangelnder Fähigkeit oder Bereitschaft keine akkuraten Antworten geben (MacKenzie & Podsakoff, 2012), die **Selbstselektionsverzerrung** (engl. self-selection bias), die aus einer nicht zufällig gezogenen Stichprobe der Grundgesamtheit resultiert (Bethlehem, 2010), die **Schweigeverzerrung** (engl. non-response bias), die durch die Unterrepräsentation bestimmter Teilnehmer in der Stichprobe entsteht (Berg, 2005), sowie **sozial erwünschtes Antwortverhalten** (engl. social desirability bias), das entsteht, wenn Teilnehmer dazu neigen, überwiegend positive Beschreibungen der eigenen Person abzugeben (Paulhus, 2002; Kemper et al., 2012). Obgleich verschiedene Gegenmaßnahmen existieren, um diese Verzerrungen zu reduzieren (Asdecker & Karl, 2023), die teilweise, wie in den jeweiligen Beiträgen ausführlich beschrieben, berücksichtigt wurden, etwa durch die Zusicherung von Anonymität zur Erhöhung der Bereitschaft, akkurate Antworten zu geben, lässt sich das Vorhandensein der Verzerrungen nie vollständig ausschließen.

Eine weitere Limitation betrifft die **Konzeptualisierung und Messung der abhängigen Variablen**. In den Beiträgen 5 und 6 wurden lediglich Verhaltensintentionen und nicht

tatsächliches Verhalten erfasst. In der Konsumentenverhaltensforschung wird jedoch seit Langem gefordert, über die Erhebung von Intentionen hinauszugehen und tatsächliche Verhaltensdaten zu berücksichtigen (vgl. z. B. Viglia et al., 2024). In den Beiträgen 3 und 4 wurde dieser Forderung nachgekommen, indem Konsumenten zwei Monate nach der ersten Befragung erneut befragt wurden, ob sie tatsächlich gewechselt haben. Dabei zeigten sich deutliche **Intentions-Verhaltens-Lücken** (engl. intention-behavior gaps), also Diskrepanzen zwischen der berichteten Wechselintention und dem berichteten Wechselverhalten, was die Problematik einer ausschließlichen Erhebung von Intentionen zusätzlich verdeutlicht (Fife-Schaw et al., 2007). Zudem ist zu berücksichtigen, dass es sich bei dem berichteten Wechselverhalten ebenfalls um **Selbstauskünfte** handelt, die den zuvor skizzierten potenziellen Verzerrungen von Befragungsstudien unterliegen. Die mit diesen Verzerrungen verbundenen Probleme könnten eine Erklärung für die stark variierende Varianzaufklärung des Kundenwechselverhaltens in bisherigen PPM-Studien sein. Während beispielsweise in Beitrag 3 lediglich 9 % und in Beitrag 4 nur 6,5 % der Varianz des Kundenwechselverhaltens erklärt werden, liegt die durchschnittliche Varianzaufklärung in der Meta-Analyse (Beitrag 2) bei 31 %, und Bansal et al. (2005) berichten sogar 57 %. Ob diese Differenzen auf inhaltliche Unterschiede zwischen verschiedenen Studienkontexten oder auf die mit Befragungsdaten verbundenen Verzerrungen zurückzuführen sind, bleibt bislang unklar. Daraus ergibt sich ein zentrales Potenzial für zukünftige Forschung: Die Validierung des PPM-Modells sollte durch den Einsatz **objektiver Verhaltensdaten** erfolgen. Solche Daten werden insbesondere in digitalen Kontexten automatisch von Unternehmen erfasst (z. B. Online-Buchungen) und könnten dazu beitragen, die Erklärungskraft des Modells für tatsächliches Verhalten präziser zu bestimmen (Blasco-Arcas et al., 2022; Viglia et al., 2024). Diesbezüglich sei jedoch angemerkt, dass der **Zugang zu objektiven Verhaltensdaten** für Forscher in der Regel nicht öffentlich möglich ist, da solche Daten von privaten Anbietern kontrolliert werden. Ohne eine entsprechende Kooperationsvereinbarung lässt sich kaum auf diese Daten zugreifen. Zwar sieht Artikel 40 des Digital Services Act der Europäischen Union vor, dass bestimmte Unternehmensdaten zu Forschungszwecken zugänglich gemacht werden müssen, jedoch gilt dies ausschließlich für sehr große Online-Plattformen und beschränkt sich auf die Identifikation und Analyse systemischer Risiken in der Europäischen Union (Verbraucherzentrale Bundesverband e. V., 2024). Eine Nutzung dieser Regelung im Rahmen der Marketingforschung erscheint daher derzeit wenig realistisch.

Eine weitere Limitation besteht darin, dass in den Beiträgen 5 und 6 die **fokalen Konstrukte isoliert** untersucht wurden, anstatt das PPM-Modell in seiner Gesamtheit zu berücksichtigen. Während in den Beiträgen 1 bis 4 das vollständige Modell mit Push-, Pull- und Mooring-Faktoren Anwendung fand, wurden in Beitrag 5 ausschließlich die Trägheitsmentalität als Mooring-Variable und in Beitrag 6 das wahrgenommene Vergnügen als Pull-Variable analysiert. Eine solche isolierte Betrachtung erlaubt zwar eine vertiefte Untersuchung einzelner Einflussfaktoren, erhöht jedoch das Risiko einer Verzerrung der Schätzer durch das **Auslassen relevanter Variablen** (engl. omitted variable bias) (Backhaus et al., 2023; Wooldridge, 2016). Da das Auslassen relevanter Variablen eine zentrale Ursache von **Endogenität** ist, die wiederum eines der größten Risiken der korrekten Modellspezifikation in empirischer Forschung darstellt (Hill et al., 2021), ist diese Limitation besonders relevant. Es sei angemerkt, dass dies nicht bedeutet, dass in den übrigen Studien kein Endogenitätsproblem vorliegt, da auch dort relevante erklärende Variablen fehlen können. Das Risiko ist in den Beiträgen 5 und 6 aufgrund der isolierten Betrachtung jedoch höher einzuschätzen.

Darüber hinaus stellt die **fehlende Repräsentativität der Ergebnisse** eine methodische Limitation dar. Die Primärdatenerhebungen in den Beiträgen 3 bis 6 basieren jeweils auf einer **Gelegenheitsstichprobe** (engl. convenience sample). Bei diesem Stichprobentyp werden Teilnehmer ungezielt nach ihrer Erreichbarkeit ausgewählt, beispielsweise Personen, die auf eine veröffentlichte Befragungseinladung reagieren (Döring, 2023; Raithel, 2008). Da die zu untersuchende Grundgesamtheit bei Gelegenheitsstichproben in der Regel a priori nicht definiert wird, was auch in den Beiträgen 3 bis 6 zutrifft, ist Repräsentativität grundsätzlich ausgeschlossen (Döring, 2023). Es sei jedoch angemerkt, dass globale Repräsentativität – die nur durch Zufallsstichproben aus definierten Grundgesamtheiten gewährleistet werden kann – nur bei populationsbeschreibenden Studien erforderlich ist, um Merkmalsausprägungen in der Grundgesamtheit präzise zu schätzen (Döring, 2023). In theoriebildenden oder hypothesenprüfenden Studien sind hingegen auch nicht-repräsentative Stichproben angemessen (Döring, 2023; Raithel, 2008).

Eine weitere damit verbundene Einschränkung betrifft die Frage, ob **Zufallsstichproben** eine notwendige Voraussetzung für **statistische Signifikanztests** darstellen: Während die pragmatische Sichtweise davon ausgeht, dass auch bei nicht-zufälligen Stichproben im Nachhinein eine fiktive Grundgesamtheit konstruiert werden könne und somit parametrische Signifikanztests zulässig

sein, betont die mathematisch-statistische Sichtweise, dass solche Tests nur bei zufallsgesteuerten Stichproben gerechtfertigt seien (Döring, 2023). Vor diesem Hintergrund plädieren manche Autoren dafür, die gängige statistische Auswertungspraxis angesichts der weit verbreiteten Verwendung nicht-zufälliger Stichproben in der akademischen Sozialforschung verstärkt auf **nicht-parametrische** statt auf parametrische **statistische Verfahren** auszurichten (Döring, 2023).

Ogleich – wie zuvor erläutert – in den Beiträgen 3 bis 6 keine Grundgesamtheit definiert wurde und die Erhebungen somit nicht repräsentativ sind, lässt sich festhalten, dass sämtliche Teilnehmende aus dem **deutschsprachigen Raum** stammen. Die gewonnenen Erkenntnisse lassen sich daher, wenn überhaupt, nur auf diesen kulturellen Kontext übertragen. Da sich **kulturelle Unterschiede** auf das Konsumverhalten auswirken können (de Mooij & Hofstede, 2002), wäre es sinnvoll, die Befunde in zukünftigen Studien in anderen kulturellen Kontexten zu replizieren, um ihre kulturelle Robustheit zu prüfen. Es sei jedoch angemerkt, dass im Rahmen der meta-analytischen Betrachtung in Beitrag 2 bereits die Kulturdimensionen nach Hofstede als Moderatoren berücksichtigt wurden, sich dabei jedoch keine signifikanten Unterschiede zeigten. Dies deutet darauf hin, dass kulturelle Einflüsse für das Kundenwechselverhalten möglicherweise keine Rolle spielen. Dieser Befund bezieht sich jedoch ausschließlich auf die Zusammenhänge zwischen den drei unabhängigen Variablen Unzufriedenheit, Attraktivität der Alternative und Wechselkosten und der abhängigen Variable Wechselintention. Andere unabhängige Variablen wurden nicht untersucht. Darüber hinaus wäre auch eine Integration der Kulturdimensionen als unabhängige Variablen statt als Moderatoren plausibel (de Mooij & Hofstede, 2002). Insofern besteht in dieser Hinsicht erheblicher Raum für zukünftige Forschung.

Eine weitere damit verbundene Limitation betrifft die **eingeschränkte externe Validität**, die sich auf die Generalisierbarkeit der Ergebnisse über die spezifischen Bedingungen der Untersuchungssituation und die untersuchten Personen hinaus bezieht (Döring, 2023; Häder, 2019). Sie verringert sich in der Regel mit zunehmender Unnatürlichkeit der Erhebungssituation im Vergleich zur alltäglichen Lebenswelt (Döring, 2023) und ist daher insbesondere im Rahmen des Laborexperiments in Beitrag 6, aber auch im Online-Experiment in Beitrag 5 kritisch zu bewerten, in denen den Teilnehmern fiktive Szenarien präsentiert wurden. Eine daraus resultierende Aufgabe zukünftiger Forschung besteht darin, die externe Validität zu erhöhen, indem Laborbedingungen möglichst alltagsnah gestaltet oder Feldexperimente durchgeführt werden (Döring, 2023; Häder, 2019).

Eine weitere Einschränkung besteht darin, dass die Erkenntnisse in allen Beiträgen ausschließlich auf dem **quantitativen Forschungsansatz** beruhen. Dieser dient in der Regel der theoriegeleiteten Überprüfung von Hypothesen anhand strukturierter Datenerhebungen und großer Stichproben (Döring, 2023; Häder, 2019). Der **qualitative Forschungsansatz** hingegen ist offen und flexibel gestaltet, untersucht wenige Fälle im natürlichen Umfeld detailliert und zielt darauf ab, theoretische Einsichten zu gewinnen sowie neue Zusammenhänge zu verstehen (Döring, 2023; Häder, 2019). Ergänzend könnten daher in zukünftiger Forschung qualitative Methoden – etwa Leitfadenterviews, Fokusgruppen oder Tagebuchstudien – eingesetzt werden, um ein tieferes Verständnis der zugrunde liegenden Motive und Entscheidungsprozesse im Kundenwechselverhalten zu gewinnen.

Eine inhaltliche Limitation besteht in der **Differenzierung zwischen Trägheit und Trägheitsmentalität**. Trägheit wird in den Beiträgen 3 und 4 definiert als „attachment to, and persistence in, using an incumbent system (i.e., the status quo), even if there are better alternatives or incentives to change“ (Polites & Karahanna, 2012, S. 22). Trägheitsmentalität wird in Beitrag 5 definiert als „a set of assumptions and beliefs that justify a disposition toward maintaining the status quo by eliminating the need to consider other options or form new intentions“ (Henderson et al., 2021, S. 351). Der Unterschied zwischen den beiden Konzepten besteht darin, dass Trägheit eine beobachtbare Verhaltensweise beschreibt, während Trägheitsmentalität die zugrunde liegenden Überzeugungen und Annahmen erfasst, die diese Verhaltensweise legitimieren. Insofern handelt es sich nicht um identische Konzepte, sondern um unterschiedliche Ebenen desselben Phänomens. Entsprechend dieses Unterschieds wich auch die Messung der beiden Konstrukte in den Beiträgen 3 und 4 von der Messung in Beitrag 5 ab. Insofern lässt sich das im Rahmen der Systematisierung der Beiträge getroffene Argument nuancieren: Beitrag 5 fokussiert nicht auf dieselbe Mooring-Variable wie die Beiträge 3 und 4, sondern auf die Trägheitsmentalität. Während Trägheit in den Beiträgen 1 und 2 als eine der am häufigsten untersuchten Mooring-Variablen identifiziert wurde und sich in den Beiträgen 3 und 4 jeweils als besonders erklärungsrelevant erwiesen hat, geht es in Beitrag 5 um deren kognitive Grundlage. Da es jedoch Ziel von Beitrag 5 war, die Antezedenzen von Trägheit zu untersuchen, ist dieser Fokus konsistent. Henderson et al. (2021) positionieren Trägheitsmentalität explizit als eine Antezedenz des von Polites und Karahanna (2012) beschriebenen Konstrukts der Trägheit.

Eine weitere inhaltliche Limitation dieser Arbeit besteht darin, dass sie – ausgehend von einem Vergleich verschiedener theoretischer Ansätze zur Erklärung von Kundenwechselverhalten in Kapitel 2.4, bei dem sich zeigte, dass in der Literatur lediglich das PPM-Modell sowie die TPB Anwendung finden – die **besondere Eignung des PPM-Modells** argumentativ begründet und dadurch die vertiefende Auseinandersetzung mit dem Modell rechtfertigt, ohne jedoch einen **empirischen Nachweis** für dessen tatsächliche Überlegenheit gegenüber der TPB in Bezug auf die Varianzaufklärung zu erbringen. Zwar wurde dargelegt, dass das PPM-Modell aufgrund seines eindeutigen intendierten Anwendungsbereichs und seiner theoretischen Fundierung in der Migrationsforschung als besonders geeigneter Ansatz zur Erklärung von Kundenwechselverhalten betrachtet werden kann – um jedoch zweifelsfrei feststellen zu können, ob das PPM-Modell der TPB hinsichtlich der Varianzaufklärung der Kundenwechselintention tatsächlich überlegen ist, wäre ein direkter Vergleich im Sinne eines **Horse-Race**²³ erforderlich (vgl. z. B. Miettinen et al., 2020). Ein solcher Vergleich gestaltet sich jedoch schwierig, solange das PPM-Modell – wie zuvor in Kapitel 5.1 ausführlich diskutiert – nicht den Charakter einer Theorie mit eindeutig formulierten Gesetzmäßigkeiten aufweist, wie dies bei der TPB der Fall ist. Hinzu kommt, dass das PPM-Modell im Rahmen der Konzeptualisierung von Push-, Pull- und Mooring-Faktoren als Konstrukte zweiter Ordnung regelmäßig die unabhängigen Variablen der TPB – Einstellung, subjektive Norm und wahrgenommene Verhaltenskontrolle (Ajzen, 1991) – als Konstrukte erster Ordnung integriert (Beiträge 3 und 4). Eine praktikable Alternative zur Durchführung eines Horse-Race bestünde im Rahmen zukünftiger Forschung insofern lediglich darin, die drei am häufigsten untersuchten Variablen des PPM-Modells (Beitrag 2) den drei unabhängigen Variablen der TPB gegenüberzustellen. Auf diese Weise ließe sich die Erklärungskraft der beiden Ansätze systematisch prüfen, ohne die zuvor skizzierten Probleme und ohne den Nachteil, dass eine größere Zahl an Variablen automatisch zu einer höheren Varianzaufklärung führt (Backhaus et al., 2023).

Abschließend sei darauf hingewiesen, dass eine **Übertragung der in dieser Arbeit gewonnenen Erkenntnisse auf andere betriebswirtschaftliche Bereiche** im Rahmen zukünftiger Forschung denkbar erscheint. Wie in Kapitel 2.1.1 dargestellt, sind Unternehmen in ein Netzwerk aus verschiedenen Stakeholdern eingebettet, deren jeweiliges Wechselverhalten für den Unternehmenserfolg von hoher Relevanz ist (Freeman, 1984; Freeman et al., 2010; Meffert et al.,

²³ Ein Horse-Race bezeichnet in diesem Zusammenhang den direkten empirischen Vergleich mehrerer Modelle hinsichtlich ihrer Varianzaufklärung desselben Phänomens (vgl. z. B. Miettinen et al., 2020).

2024). Während die vorliegende Arbeit den Fokus auf das Kundenwechselverhalten gelegt hat, ließen sich die gewonnenen Erkenntnisse beispielsweise auf das Wechselverhalten von Mitarbeitern übertragen, die über einen Arbeitgeberwechsel entscheiden. Darüber hinaus bietet auch der **B2B-Kontext** Anknüpfungspunkte. So lässt sich das PPM-Modell beispielsweise zur Untersuchung des Wechselverhaltens von Unternehmen gegenüber ihren Lieferanten anwenden (Suh & Kim, 2018). Wechselverhalten im B2B-Kontext wurde insgesamt bislang jedoch nur wenig empirisch unter Anwendung des PPM-Modells untersucht (Beitrag 2) und bietet somit ein Potenzial für zukünftige Forschung. Obwohl sich die Determinanten des Wechselverhaltens je nach Stakeholder unterscheiden, verbindet sie die gemeinsame Grundstruktur einer Entscheidung zwischen Status-quo und Alternative. Vor diesem Hintergrund bieten die Ergebnisse dieser Arbeit einen Ausgangspunkt, um Wechselverhalten auch in weiteren Bereichen der Betriebswirtschaftslehre systematisch zu untersuchen.

6 Fazit

Die vorliegende Dissertation widmete sich dem Ziel, ein vertieftes Verständnis des Kundenwechselerhaltens im digitalen Dienstleistungskontext zu entwickeln. Der Ausgangspunkt war die Beobachtung, dass die heutigen Rahmenbedingungen für Unternehmen unter anderem von drei zentralen Entwicklungen – dem Wandel vom Verkäufer- zum Käufermarkt, der Tertiarisierung sowie der Digitalisierung – geprägt sind, weshalb ebendieses Verständnis bedeutsam ist.

Zur Erreichung dieses Ziels wurden drei zentrale Forschungsfragen adressiert. Zur Beantwortung der ersten Forschungsfrage *„Wie lässt sich Kundenwechselerhalten im Dienstleistungskontext definieren und von verwandten Konstrukten abgrenzen?“* wurde Kundenwechselerhalten im Dienstleistungskontext definiert und vom Begriff der Kundenabwanderung abgegrenzt. Dabei wurde herausgestellt, dass Kundenwechselerhalten eine Kundenabwanderung voraussetzt und somit als übergeordneter Begriff zu verstehen ist. Zudem wurde der Zusammenhang zwischen Kundenloyalität und Kundenwechselerhalten aufgezeigt, um die Notwendigkeit einer eigenständigen theoretischen Betrachtung zu unterstreichen.

Zur Beantwortung der zweiten Forschungsfrage *„Welche theoretischen Ansätze eignen sich zur Erklärung des Kundenwechselerhaltens im Dienstleistungskontext?“* wurden verschiedene theoretische Ansätze zur Erklärung von Kundenwechselerhalten dargestellt und miteinander verglichen. Dabei zeigte sich, dass das PPM-Modell in der Literatur am häufigsten verwendet wird und aufgrund seines eindeutigen intendierten Anwendungsbereichs sowie seiner aus der Migrationsforschung abgeleiteten theoretischen Fundierung am besten geeignet ist, um Kundenwechselerhalten im Dienstleistungskontext zu erklären.

Zur Beantwortung der dritten Forschungsfrage *„Was sind die Determinanten des Kundenwechselerhaltens im digitalen Dienstleistungskontext?“* lieferten die Beiträge 1 und 2 zunächst meta-analytische Evidenz zum PPM-Modell im allgemeinen Dienstleistungskontext. Aufbauend darauf untersuchten die Beiträge 3 bis 6 das Kundenwechselerhalten im digitalen Dienstleistungskontext. Insgesamt zeigte sich, dass der theoretische Ansatz des PPM-Modells auch im digitalen Dienstleistungskontext einen hohen Erklärungsgehalt aufweist, wobei Push-, Pull- und Mooring-Faktoren je nach konkretem Anwendungsfall in unterschiedlichem Maße zur Erklärung der abhängigen Variablen beitragen.

Basierend auf den Ergebnissen wurden, in Bezugnahme auf die zentralen Interessensgruppen des Marketings nach der modernen, erweiterten Definition, Implikationen auf theoretischer, praktischer sowie gesellschaftlich-politischer Ebene abgeleitet.

Aus theoretischer Perspektive ergeben sich mehrere Ansatzpunkte zur Weiterentwicklung des PPM-Modells: die Formulierung allgemeiner Gesetzmäßigkeiten, eine einheitliche Konzeptualisierung von Push-, Pull- und Mooring-Faktoren, eine überarbeitete Definition des Mooring-Faktors, eine Erweiterung um affektive Variablen sowie die Weiterentwicklung vom Partial- zum Totalmodell. Darüber hinaus ergeben sich Ansätze zur Integration angrenzender Theorien – der Theorie des regulatorischen Fokus, der Status-quo-Bias-Theorie und der Customer-Inertia-Marketing-Theorie – sowie die Möglichkeit, das PPM-Modell in das Churn-Management zu integrieren.

Für die betriebswirtschaftliche Praxis werden verschiedene Strategien dargelegt, mit denen Kundenwechselverhalten gezielt beeinflusst werden kann. Diese Strategien lassen sich in defensive Strategien, die darauf abzielen, Wechsel im bestehenden Kundenstamm zu verhindern und somit die Kundenbindung betreffen, und offensive Strategien, die darauf ausgerichtet sind, Wechsel im Kundenstamm der Wettbewerber auszulösen und somit die Kundenakquisition betreffen, unterteilen.

Auf gesellschaftlich-politischer Ebene wird verdeutlicht, wie die gewonnenen Erkenntnisse im Kontext der Nachhaltigkeitstransformation und der digitalen Transformation Anwendung finden können, indem aufgezeigt wird, wie die Verbraucherpolitik durch den gezielten Einsatz regulatorischer, ökonomischer und befähigender Instrumente zum Gelingen dieser Transformationen beitragen kann.

Schließlich wurden aus den identifizierten methodischen und inhaltlichen Limitationen verschiedene Ansatzpunkte für zukünftige Forschung aufgezeigt, an die weiterführende Studien gezielt anknüpfen können.

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