Modeling Digital Technology Adoption Across Analytical Levels: A Multilevel Socio-Technical Analysis

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List of Abbreviations

A/AT	Attitude
ADONIS	Business Process Management (BPM) software tool
ADSRM	Agile Design Science Research Methodology
AI	Artificial Intelligence
AU	Actual Use
α	Cronbach's α
AVE	Average Variance Extracted
BIR	International Conference on Perspectives in Business Informatics Research
BI	Behavioral Intention to use
BITKOM	Bundesverband Informationswirtschaft, Telekommunikation und neue Medien (Federal Association for Information Technology, Telecommunications and New Media)
BMWK	Bundesministerium für Wirtschaft und Klimaschutz (Federal Ministry for Economics and Climate Action)
BPMN	Business Process Model and Notation
β	Path Coefficient
CA	Cronbach's Alpha
C19A	COVID-19 Awareness
CDSS	Consumer decision support system
cf.	confer (compare)
CMB	Common Method Bias
COVID-19	Coronavirus Disease 2019
CR	Composite Reliability
CRM	Customer Relationship Management
CV	Convergent Validity
DOI	Digital Object Identifier
DSRM	Design Science Research Methodology
DV	Discriminant Validity
ECIS	European Conference on Information Systems
EFRE	European Regional Development Fund
EPCs	Event-driven Process Chains
ERD	Entity-Relationship Diagram

ERP	Enterprise Resource Planning
f^2	Cohen's F-squared
FLC	Fornell-Larcker Criterion
GDPR	General Data Protection Regulation
H	Hypothesis
HTMT	HeterotraiT-MonotraiT ratio of correlations
HVAC	Heating, Ventilation, and Air Conditioning
ICR	Internal Consistency Reliability
IJMC	International Journal of Mobile Communications
IS	Information Systems
IR	Indicator Reliability
λ	Lambda (Factor Loading)
LISREL	Linear Structural Relations
MGA	Multi-Group Analysis
n	Sample size
ns	not significant
n. pag.	no pagination
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
p	probability value
PC	Perceived Costs
PCA	Principal Component Analysis
PE	Perceived Enjoyment
PEOU	Perceived Ease Of Use
PF	Perceived comFort
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modeling
PLS-MGA	Partial Least Squares Multi-Group Analysis
PR	Perceived Risk
PS	Perceived Security
PU	Perceived Usefulness
PV	Perceived Value
Q^2	Q-squared (Predictive Relevance)
R^2	R-squared (Coefficient of determination)

RQ	Research Question
ρc	Composite Reliability
SEM	Structural Equation Modeling
SERM	Structures Entity Relationship Model
SHT	Smart Home Technology
SN	Subjective Norm(s)
SNS	Social Network Site
SNSs	Social Network Sites
SR	Social Reasons
SRMR	Standardized Root Mean Square Residual
TAM/TAM2	Technology Acceptance Model
TPB	Theory of Planned Behavior
TR	TRust
TS	TechnoStress
UTAUT 2	Unified Theory of Acceptance and Use of Technology 2
VIF	Variance Inflation Factor
VCMR	Vacuum Cleaners and Mopping Robots
VHB	German Academic Association for Business Research
VHB-JOURQUAL3	Journal Quality Ranking (Version 3) of the VHB
WFT	Wearable Fitness Trackers
w	Weights

1. Introduction

1.1 Digitalization in Economy and Society

Digitalization has become a structurally influential force across economic and societal domains. Rather than representing a mere shift from analog to digital formats, digitalization entails deep structural changes in how individuals interact, how organizations function, and how cities and societies evolve (Brennen & Kreiss, 2016, pp. 1–11; Tilson et al., 2010, pp. 748–759). It reconfigures communication, labor, consumption, governance, and even identity construction, making it one of the most pervasive change processes of the 21st century. From an economic perspective, digitalization enables new forms of value creation, disrupts traditional business models, and introduces digital platforms and ecosystems as central actors in modern markets (Bharadwaj et al., 2013, pp. 471–482; Parker et al., 2016, pp. 133–148). From a societal perspective, it reshapes how people access information, relate to institutions, and organize collective action (Van Dijck et al., 2018). To clarify these different dimensions, the following section distinguishes between digitization, digitalization, and digital transformation.

The term *digitization* refers to the "material process of converting analog streams of information into digital bits" (Brennen & Kreiss, 2016, p. 1). *Digitalization*, in contrast, describes the use of digital technologies to redesign business processes and create new value propositions (Legner et al., 2017, pp. 301–308). *Digital transformation* encompasses organization-wide strategic change aimed at fundamentally improving an entity through combinations of information, computing, communication, and connectivity technologies (Vial, 2021, pp. 13–66). This, in turn, requires firms to develop a coherent digital transformation strategy that aligns technology adoption with business goals and organizational structures (Matt et al., 2015, pp. 339–343).

At its core, digitalization involves the integration of digital technologies into existing systems, leading to dynamic socio-technical configurations shaped by technological affordances, user practices, and institutional contexts (Yoo et al., 2012, pp. 1398–1408). Digital systems such as enterprise resource planning (ERP), customer relationship management (CRM), digital twins, and smart city infrastructures illustrate this embeddedness. From algorithmic decision-making and smart infrastructures to social

media platforms and wearable health technologies, digital innovation mediates everyday life in increasingly complex and sometimes opaque ways (Kitchin, 2014, pp. 1–14; Zuboff, 2023, pp. 203–213).

Importantly, digitalization is not a purely technical process but unfolds within social structures and value systems and, therefore, inherently normative and contested (Orlikowski, 2000, pp. 404–428; Van Dijck et al., 2018). As such, it brings both opportunities and challenges: it can enable participation, transparency, and efficiency but also amplify surveillance, exclusion, or technostress (Ayyagari et al., 2011, pp. 831–858). Understanding digitalization thus requires interdisciplinary approaches that account for both human agency and technological evolution. The field of Information Systems (IS) research plays a critical role in this regard by analyzing the co-evolution of technology and organization, the socio-technical dynamics of IT adoption, and the implications of digital innovation for management, policy, and societal well-being (Gregor & Hevner, 2013, pp. 337–355).

From an *economic* perspective, digitalization affects productivity, market efficiency, and innovation capacity. It allows for the automation of routine tasks, the emergence of new platform-based business models and the internationalization of services and digital ecosystems (Bharadwaj et al., 2013, pp. 471–482; European Central Bank, 2024). Small and medium-sized enterprises, in particular, can gain new competitive advantages by adopting cloud services, AI-powered analytics, or digital marketplaces. Moreover, the rise of data as a core economic resource, often referred to as “the new oil”, highlights the importance of data governance and digital competencies in the modern knowledge economy (Wamba et al., 2015, pp. 234–246).

From a *societal* perspective, digitalization influences how people engage in education, health care, mobility, and democratic processes. It enables personalized learning, telemedicine, and digital participation but also risks reinforcing the digital divide, data misuse, and algorithmic bias (Van Zoonen, 2016, pp. 472–480). Questions of digital inclusion, trust, privacy, and ethical AI are becoming central to policy debates worldwide (Floridi et al., 2018, pp. 689–707). In cities, digitalization manifests in smart governance, intelligent transportation, and participatory urban planning, offering both efficiencies and new modes of citizen engagement (Bolívar & Meijer, 2016, pp. 673–692; Nam & Pardo, 2011, pp. 282–291).

Despite the growing body of research on digitalization, existing studies often remain confined to specific analytical levels. For example, research on technology acceptance predominantly focuses on individual users (Davis, 1989, pp. 319–340; Venkatesh et al., 2003, pp. 425–478), while studies on digital transformation examine organizational change (Vial, 2021, pp. 13–66). Urban informatics research explores smart cities and digital infrastructures (e.g., Nam & Pardo, 2011, pp. 282–291), and societal-level analyses address datafication and surveillance (Van Dijck, 2014, pp. 197–208). While these research streams provide valuable insights, they typically focus on isolated levels. However, digitalization unfolds simultaneously across and between these levels. Individual perceptions influence organizational implementation; urban infrastructures shape citizen experiences; and societal discourses frame technological legitimacy. As a result, single-level analyses of digitalization may lead to fragmented explanations that overlook relevant contextual relationships. A multilevel perspective is therefore useful to better account for how digital technology adoption and evaluation vary throughout analytical levels. This work contributes to this perspective by developing a multilevel analytical framework and applying it in different six empirical studies.

While digitalization provides the overarching transformation framework, the empirical investigations operationalize digitalization through the analysis of technology adoption processes at different analytical levels. In this sense, technology adoption serves as an analytically observable manifestation of broader digitalization processes within the economy and society.

1.2 Objectives

This dissertation empirically investigates how digital technologies are adopted, embedded, and evaluated across different analytical levels within economy and society. While digitalization is often framed as a large-scale transformation process, its practical manifestation frequently occurs through concrete adoption decisions, contextual integration, and user evaluation in specific domains. Building on established research in IS on technology acceptance and use (Davis, 1989, pp. 319–340; Venkatesh et al., 2003, pp. 425–478), this research conceptualizes digitalization as a socio-technical phenomenon that can be modeled through theoretically grounded constructs.

Although substantial research has examined technology acceptance, digital transformation, and smart urban infrastructures, many studies remain confined to single levels of analysis or isolated application domains. At the same time, methodological challenges, particularly regarding construct measurement and model specification in Partial Least Squares Structural Equation Modeling (PLS-SEM), have received increasing attention but remain subject to ongoing discussion (Hair et al., 2017; Sarstedt et al., 2016, pp. 3998–4010). In particular, the distinction between formative and reflective measurement has been highlighted as conceptually demanding, with implications for the interpretations of empirical results (Jarvis et al., 2003, pp. 199–218; Petter et al., 2007, pp. 623–656). These methodological considerations are especially relevant in multilevel research settings, where constructs may differ across analytical levels and require careful conceptualization and specification. The present research contributes to these discussions by combining empirical analyses of digital technology adoption across different analytical levels of analysis with a systematic and theory-informed approach to construct specification and model development in PLS-SEM.

Against this background, the overarching objective of this dissertation is:

To model and empirically examine how digital technologies are adopted and evaluated across individual, organizational, urban, and societal contexts, and to strengthen methodological rigor in IS research through structured guidance on measurement specification and model development.

To achieve this objective, the dissertation pursues five interrelated research aims that reflect the multilevel analytical perspective adopted in this work. Each aim addresses a specific empirical context while contributing to a broader understanding of digital technology adoption and evaluation across analytical levels.

1. To analyze cultural and psychological determinants of technostress and social network usage behavior across national contexts (Paper 1).
2. To investigate key drivers of smart home technology adoption, focusing on trust, perceived value, and lifestyle integration (Paper 2).
3. To analyze adoption intentions toward wearable fitness trackers in a public health context and assess the relative importance of perceived value and contextual awareness (Paper 3).

4. To design and empirically evaluate a city app as a digital artifact aimed at supporting urban revitalization and citizen engagement (Paper 4).
5. To examine the structural determinants of perceived urban attractiveness using multivariate statistical modeling, thereby situating digital elements within broader urban perception structures (Paper 5).

In addition to these domain-specific investigations, the dissertation provides a methodological contribution:

6. To develop and empirically demonstrate a structured decision framework for measurement model specification in PLS-SEM, highlighting the importance of theory-consistent construct modeling in IS research (Paper 6).

Taken together, these studies contribute to answering the following research question:

How can digital technology adoption be empirically analyzed across multiple analytical levels, and how does theory-consistent measurement specification contribute to the validity of these analyses?

By integrating multilevel analysis with methodological rigor, the dissertation contributes to IS research in three ways. It demonstrates that digital technology adoption cannot be adequately explained within isolated analytical levels, but requires a cross-level perspective that considers the interplay between individual, contextual, and structural mechanisms. First, consistent with discussions of multilevel theorizing (Klein et al., 1999, pp. 248–253), it examines digital technology phenomena across analytically distinct yet empirically interconnected levels, thereby highlighting relationships between individual behavior, urban contexts, and broader socio-technical structures. Second, it provides context-sensitive empirical evidence across diverse application domains, including social network usage, smart home technologies, wearable fitness tracking, and urban digital infrastructures, thereby linking individual, urban, and broader socio-technical perspectives. Third, it strengthens methodological transparency in PLS-SEM-based research by advancing structured guidance for formative and reflective construct specification, thereby supporting more valid and theory-consistent model development in IS research.

1.3 Research Design and Structure

This dissertation follows a cumulative research design and comprises six individual studies that are conceptually connected through a shared empirical and methodological focus. Three of the papers have been published in peer-reviewed outlets, and the remaining three are currently available as working papers that further extend the analytical and methodological scope of this work. While the empirical contexts vary, the studies are unified by their focus on empirically modeling digital technology phenomena and reflecting on the methodological foundations of such analyses in Information Systems research. Table 1 provides an overview of the publication status, outlets, and methodological approaches of the six underlying papers.

Table 1. *Publication Status, Outlets, and Analytical Approaches of Included Papers*

Paper	Title (Shortened)	Outlet	VHB Ranking	Publication Status	Analytical Approach
1	Technostress and Culture on Social Network Sites	International Journal of Mobile Communications (2024)	C	Published	PLS-SEM
2	Acceptance of Smart Home Technology	Conference on Perspectives in Business Informatics Research (2020)	C	Published	PLS-SEM
3	Wearable Fitness Trackers and COVID-19	Conference on Perspectives in Business Informatics Research (2021)	C	Published	PLS-SEM
4	Revitalizing the City Centers – City App	Working Paper	-	Working Paper	Artifact Evaluation & PLS-SEM
5	Urban Attractiveness through Digital Integration	Working Paper	-	Working Paper	Principal Component & Regression Analysis
6	Measurement Specification in PLS-SEM	Working Paper	-	Working Paper	Conceptual & Empirical Modeling

Note. VHB Ranking refers to VHB-JOURQUAL 3 classification.

Rather than presenting a single monolithic theory of digitalization, the dissertation builds its contribution through context-sensitive empirical investigations across multiple

analytical levels. Each study is explicitly linked to the multilevel analytical framework, addressing digital technology adoption and evaluation from a specific analytical level and thereby contributing to a coherent cross-level perspective throughout the dissertation. Three studies examine technology adoption and evaluation at the individual level, focusing on cultural influences, trust, perceived value, and technostress. Two studies address digital phenomena in urban environments, combining artifact evaluation and multivariate modeling to analyze how digital elements interact with broader structural characteristics of city centers. Complementing these domain-specific analyses, one study develops a structured decision framework for measurement specification in PLS-SEM, thereby contributing to methodological rigor and transparency in IS research. Together, the six studies form a coherent research program that combines multilevel empirical analysis with systematic methodological reflection.

The dissertation is structured as follows. Chapter 2 establishes the conceptual and methodological foundations by outlining the socio-technical understanding of digitalization adopted in this work, introducing the multilevel analytical perspective, and presenting the theoretical and methodological anchors that guide the empirical investigations. Chapters 3 and 4 contain the empirical studies, each presented as a self-contained paper while embedded within the overarching research logic. Chapter 5 provides the methodological reflection on measurement specification in PLS-SEM and develops the structured decision framework that complements the empirical analyses. Chapter 6 integrates the findings across studies, synthesizes the results at a higher level of abstraction, and discusses their theoretical and practical implications. Finally, Chapter 7 concludes the dissertation by summarizing the main contributions and outlining avenues for future research.

2. Analytical Framing of Digitalization

Building on the problem outlined in Chapter 1, this chapter develops the conceptual and methodological foundation required to analyze digital technology adoption across multiple analytical levels (individual, organizational, urban, and societal).

2.1 Conceptual Foundations

In this dissertation, digitalization is conceptualized as the integration of digital technologies into economic and societal practices, resulting in new configurations of interaction, coordination, and value creation. However, the effects of digital technologies do not unfold independently. Instead, they are shaped by the interplay between technological artifacts, human actors, and institutional environments. From a socio-technical perspective, technologies are neither neutral tools nor deterministic forces; their meaning and impact emerge through processes of use, interpretation, and organizational embedding (Orlikowski, 2000, pp. 404–428).

While digitalization is frequently associated with large-scale transformation narratives, empirical evidence suggests that digital technologies are often incrementally embedded into existing material, organizational, and social arrangements rather than fully replacing them (Orlikowski & Iacono, 2001, pp. 121–134; Yoo et al., 2012, pp. 1398–1408). This is particularly visible in urban environments, where digital infrastructures operate alongside established spatial and functional characteristics (Tilson et al., 2010, pp. 748–759), and in domestic contexts, where adoption decisions are embedded in everyday routines and value perceptions (Orlikowski & Iacono, 2001, pp. 121–134).

This work positions itself within IS research as an empirically grounded, cross-level theorizing approach to digitalization that integrates contextual sensitivity with methodological transparency across analytical levels. It demonstrates that digitalization unfolds through context-specific adoption and evaluation processes that vary throughout domains and analytical levels. The analytical focus lies on how digital technologies are adopted, evaluated, and embedded within specific domains, and how these processes can be empirically operationalized using theoretically grounded constructs. By systematically modeling these processes, this research shows that digitalization cannot be understood as a uniform transformation process, but instead requires context-sensitive and level-specific

analysis. This perspective enables a systematic examination of digital phenomena while avoiding deterministic or overstated transformation narratives.

2.2 A Multilevel Perspective

To systematically analyze digital technology phenomena across heterogeneous empirical contexts, this research adopts a multilevel analytical perspective (Klein et al., 1999, pp. 248–253) that acknowledge cross-level interdependencies. It distinguishes four analytical levels: individual, organizational and institutional, urban, and societal. These levels represent distinct contexts of technology adoption, evaluation, and embedding, reflecting different mechanisms of digitalization. Digitalization is thus conceptualized as a cross-level phenomenon shaped by interactions between these levels.

At the individual level, digital technologies are experienced, interpreted, and enacted by users. Key constructs such as adoption intentions, perceived usefulness, technostress, trust, and perceived value explain how individuals integrate digital technologies into everyday practices. The empirical studies examine these mechanisms across contexts, including social network usage, smart home adoption, and wearable fitness trackers.

At the organizational and institutional level, digital technologies are embedded in implementation processes, governance structures, and institutional arrangements. This level captures how organizations structure technology use and how institutional contexts shape these processes. While no study exclusively focuses on this level, it serves as an intermediary layer linking individual behavior with broader implementation contexts.

At the urban level, digital technologies interact with spatial infrastructures and collective patterns of use. The analytical focus shifts from individual intention to collective implementation, infrastructural integration, and contextual interaction within urban environments. The city app study and the analysis of urban attractiveness illustrate how digital elements relate to the spatial and functional characteristics of city centers.

At the societal level, digital technologies are situated within broader cultural, regulatory, and institutional frameworks that shape their interpretation and use. Although the empirical studies in the present research do not directly model macro-level institutions, societal conditions such as cultural differences or public health crises act as framing contexts that influence technology-related perceptions and decisions.

These cross-level dynamics link individual behavior, organizational practices, urban infrastructures, and societal frameworks. Individual adoption decisions contribute to organizational implementation and urban integration, while institutional frameworks shape how technologies are perceived and utilized. A methodological reflection, represented by Paper 6, complements this structure by addressing issues of construct specification and model development across all levels.

Figure 1 illustrates the multilevel socio-technical framework and positions the individual studies according to their primary analytical focus:

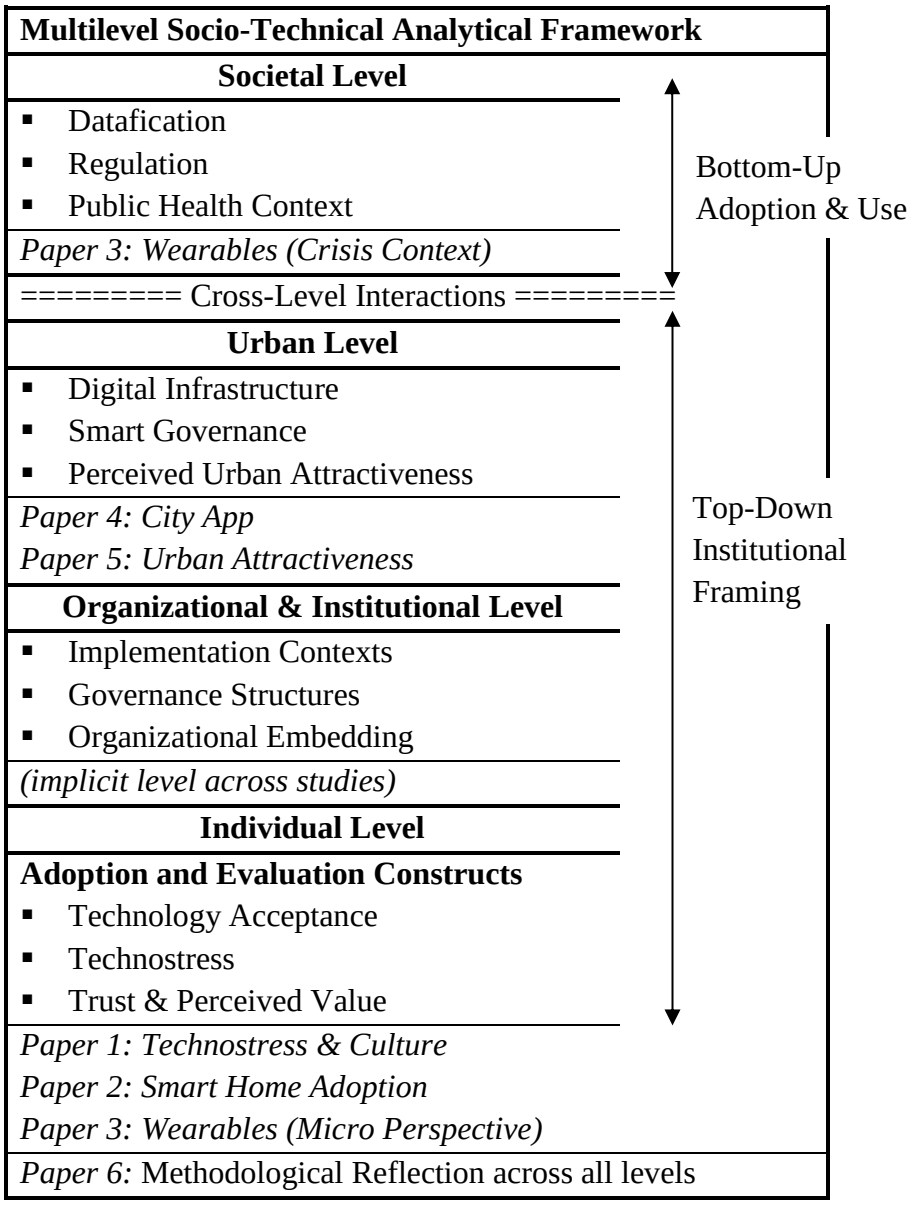


Figure 1. *Multilevel Socio-Technical Analytical Framework*

2.3 Theoretical Anchors

The empirical investigations in this dissertation are grounded in established theoretical frameworks within Information Systems research. Rather than developing new grand theory, the studies build on and extend existing explanatory models that allow digital technology phenomena to be operationalized through measurable constructs and structured relationships.

A central foundation is technology acceptance research, particularly the Technology Acceptance Model (TAM) (Davis, 1989, pp. 319–340) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003, pp. 425–478). These frameworks provide parsimonious yet robust explanations for technology adoption behavior by linking perceived usefulness, ease of use, social influence, and facilitating conditions to behavioral intentions and usage outcomes. Across multiple studies in this work, these constructs serve as theoretical anchors for modeling adoption intentions in diverse contexts, including social network sites, smart home technologies, and wearable fitness trackers. They are not treated as universal predictors but as adaptable modeling templates that are extended and contextually specified.

Complementing technology acceptance theory, research on technostress (Ragu-Nathan et al., 2008, pp. 417–433) informs the analysis of digital strain in social network environments. Technostress captures the negative psychological effects associated with information overload, constant connectivity, and technological complexity. By integrating technostress into adoption models, the dissertation acknowledges that digitalization does not only generate utility, but may also produce cognitive and emotional burdens that shape user behavior.

In addition, constructs such as trust and perceived value play a central role in contexts where technologies are embedded in domestic or health-related environments. Trust theory (Gefen et al., 2003, pp. 307–321) and value-based perspectives on technology adoption allow for a more nuanced understanding of how users evaluate digital artifacts beyond functional performance. These constructs are particularly relevant in smart home and wearable technology contexts, where privacy, security, and perceived benefits intersect. In the urban context, digital technologies are analyzed not primarily as objects of individual adoption but as elements interacting with existing spatial and infrastructural

qualities. Here, multivariate modeling serves to position digital integration within broader urban perception structures rather than attributing isolated causal effects to digital variables.

While these theories primarily operate at the individual level, they are embedded within a broader socio-technical understanding of digitalization. Technologies are not adopted in isolation but within institutional, cultural, and situational contexts that shape interpretation and legitimacy. Accordingly, socio-technical systems theory provides an overarching lens that integrates individual-level constructs with contextual and structural conditions.

Together, these theoretical anchors enable a structured yet flexible modeling of digital technology phenomena across multiple empirical domains while maintaining theoretical consistency and methodological clarity.

2.4 Methodological Architecture

The empirical foundation of this dissertation is characterized by a modeling-oriented research design that combines structural equation modeling, multivariate statistical analysis, and artifact evaluation. Across the six studies, methodological choices are guided by the aim of theory-consistent construct operationalization and transparent model specification rather than methodological novelty.

A central analytical approach employed in multiple studies is Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is particularly suitable for modeling complex relationships between latent constructs, especially in contexts where theoretical development and prediction are intertwined (Hair et al., 2017). In this work, PLS-SEM is applied to examine technology acceptance, technostress, trust, and perceived value across different domains. The method enables the simultaneous estimation of measurement and structural models, allowing for a nuanced assessment of construct validity and relational patterns.

However, methodological rigor extends beyond statistical estimation. A recurring challenge in empirical IS research concerns the specification of measurement models, particularly the distinction between formative and reflective constructs (Jarvis et al., 2003, pp. 199–218). Misalignment between theoretical meaning and statistical modeling

can lead to conceptually distorted interpretations, even when statistical diagnostics appear acceptable. To address this issue systematically, one study within this dissertation develops a structured decision framework for measurement specification in PLS-SEM. By combining conceptual criteria with empirical illustration, this contribution strengthens theory-consistent construct modeling and enhances transparency in reporting practices.

In addition to structural equation modeling, the dissertation employs multivariate techniques such as principal component analysis and regression modeling in the analysis of urban attractiveness. These methods allow for the identification of latent perception structures and the examination of relative explanatory contributions of digital and non-digital factors. Here, the emphasis lies on positioning digital integration within broader structural patterns rather than isolating singular technological effects.

The evaluation of the city app further complements the quantitative modeling approach by incorporating artifact-oriented analysis. Although grounded in empirical measurement, this study demonstrates how digital artifacts can be assessed in real-world contexts, linking design decisions to behavioral intentions and usage-related outcomes.

Taken together, the methodological architecture of this work reflects a coherent commitment to construct clarity, contextual sensitivity, and analytical transparency. Rather than privileging one methodological paradigm, the research design aligns methodological choices with the nature of the empirical phenomenon under investigation, while maintaining consistent standards of theoretical and statistical rigor.

3. Individual Technology Use

The increasing ubiquity of digital technologies has transformed how individuals communicate, manage domestic environments, and monitor their health. Building on the multilevel framing introduced in Chapter 2, this chapter examines digital technology adoption at the individual level across three domains: social networking sites (SNSs), smart home technologies, and wearable fitness trackers. Despite contextual differences, all three are embedded in everyday routines and require individual evaluation and behavioral intention.

The first study, *Toward an Understanding of Individualism, Collectivism, and Technostress on Social Network Sites*, analyzes how cultural values shape technostress on SNSs. Drawing on Hofstede's cultural dimensions and technostress theory, it shows that individualism is associated with higher social overload and compulsive use, whereas collectivism mitigates these effects. The comparison between China and Germany highlights the role of culture in digital stress responses.

The second study, *The Acceptance of Smart Home Technology*, examines household adoption by extending the Technology Acceptance Model (TAM) with trust, control, privacy, and emotional attachment. Results indicate that perceived usefulness and trust are the strongest predictors of use intention, while autonomy perceptions also contribute.

The third study, *Using Wearable Fitness Trackers to Detect COVID-19?!*, situates adoption in a public health context. Although wearable fitness trackers promise lifestyle optimization and disease monitoring, adoption remains moderate. Based on a survey of 207 users and non-users, the study identifies perceived value as the central driver of intention, while COVID-19 awareness shows no significant effect. The findings illustrate how crisis framing interacts with established acceptance constructs.

Taken together, the three studies demonstrate that individual-level adoption is shaped by cultural values, cognitive and emotional evaluations, and situational framing conditions. In line with the overarching objective of modeling digital technology adoption across analytical levels, this chapter provides empirically grounded insights into the micro-level mechanisms through which digitalization manifests in everyday life.

Paper 1: **Toward an Understanding of Individualism, Collectivism, and Technostress on Social Network Sites: Evidence from China and Germany**

Authors: Nils Bernhard Bienek, Christina Gross, Richard Lackes, and Markus Siepermann

Outlet: International Journal of Mobile Communications, Vol. 23, Issue 3

Publication Status: Published, April 05, 2024

DOI: https://doi.org/10.1504/IJMC.2024.137767

Abstract: Social network sites (SNSs) are popular worldwide, but despite the ongoing process of globalisation, usage varies widely from country to country. Reasons for this are manifold, and require further research. In addition to different platforms, cultural differences can also lead to different levels of usage. This paper aims to examine the different factors which influence SNS usage. For this, a survey of 281 Chinese and German users was conducted. While China is the archetype of a collectivist society, Germany is considered to be more individualistic. The results show that social reasons and technostress (TS) influence usage behaviour. In particular, the influence of social reasons on subjective norms and further on perceived usefulness towards SNSs is greater among Chinese users. Interestingly, TS seems to be non-culturally influenced.

Keywords: Facebook, Qzone, Renren, Germany, China, technostress, social network sites, SNSs, individualism, collectivism

Paper 2: **The Acceptance of Smart Home Technology**

Authors: Christina Gross, Markus Siepermann, and Richard Lackes

Outlet: Perspectives in Business Informatics Research
19th International Conference on Business Informatics Research, BIR 2020, Vienna, Austria, September 21–23, 2020, Proceedings, pp. 3–18, Lecture Notes in Business Information Processing, Vol. 398

Publication Status: Published, October 11, 2020

DOI: https://doi.org/10.1007/978-3-030-61140-8_1

Abstract: The market for smart home technology (SHT) has increased rapidly and is said to do so during the next years. In particular, comfort and security features are the main focus of vendors. This paper aims to examine the different influencing factors that have an impact on the adoption decision of consumers. For this, a survey was conducted among 327 German consumers. Results show that perceived security and comfort are significant influencing factors. In particular, control functions play an important role. In contrast, neither usability of SHT nor costs show a noteworthy impact on the adoption decision, although costs are expected to be high.

Keywords: Smart Home Technology, Perceived Security, Perceived Comfort, Perceived Costs, Technology Acceptance Model

Paper 3: **Using Wearable Fitness Trackers to Detect COVID-19?!**

Authors: Christina Gross, Wladimir Wenner, and Richard Lackes

Outlet: Perspectives in Business Informatics Research
20th International Conference on Business Informatics Research, BIR 2021, Vienna, Austria, September 22–24, 2021, Proceedings, pp. 51–65, Lecture Notes in Business Information Processing, Vol. 430

Publication Status: Published, September 08, 2021

DOI: https://doi.org/10.1007/978-3-030-87205-2_4

Abstract: Wearable Fitness Trackers (WFTs) could both lead to healthier lifestyles and be suitable for tracking infectious diseases. However, though they have existed for many years they are still not prevalent. We developed a research model which was theoretically embedded in technology acceptance research, then analyzed the data collected through a survey of 207 WFT users and non-users. Our findings suggest that, in respect to both users and non-users, perceived value is the strongest driver of usage intention. Furthermore, we found significant differences between male and female participants. Unfortunately, we were not able to confirm a relation between Covid-19 awareness and WFT usage intention. Our study provides relevant findings to manufacturers and insights into the consumer WFT needs.

Keywords: Wearable Fitness Trackers, COVID-19, Technology Acceptance

4. Digital Technologies in Urban Contexts

Digital technologies increasingly shape urban environments, yet their effects on urban vitality and attractiveness remain context-dependent. Within the multilevel analytical framework developed in Chapter 2, this chapter focuses on digitalization at the urban level, examining how digital tools interact with spatial structures and collective perceptions of city centers.

Urban digitalization is often framed as a response to structural challenges such as retail decline and changing consumption patterns. However, digital technologies do not operate autonomously; their impact depends on how they are embedded within existing spatial and institutional configurations. Rather than assuming deterministic effects, this chapter analyzes digital elements as components within broader urban systems.

The first study, *Revitalizing the City Centers – Design and Evaluation of a City App*, adopts a design science perspective to develop and evaluate a digital artifact aimed at enhancing urban engagement. Using the Agile Design Science Research Methodology, the study shows that personalized and location-based features positively influence visit intention and length of stay, whereas gamification plays a secondary role. The complementary section (4.1.7) visualizes the underlying design logic through process and entity models.

The second study, *A Data-Driven Structural Analysis of Perceived Urban Attractiveness under Digital Transformation*, applies principal component analysis and regression modeling to survey data from six cities. The findings indicate that structural qualities such as safety, cleanliness, and accessibility remain dominant predictors of attractiveness, while digital elements enhance perception only when embedded in coherent spatial contexts.

Taken together, the studies demonstrate that urban digitalization operates through contextual embedding rather than technological substitution. In line with the overarching objective of modeling digital technology phenomena across analytical levels, this chapter illustrates how digital elements interact with structural urban configurations.

Paper 4: Revitalizing the City Centers – Design and Evaluation of a City App

Authors: Christina Gross, Richard Lackes

Abstract: For many years, cities in rural regions have suffered from the disappearance of local owner-operated retail stores, followed by high vacancy rates in city centers and a subsequent loss of attractiveness. The rise of digital technologies over the past decades, with the rise of e-commerce and the COVID-19 pandemic, has accelerated this development even further. However, the potential of digital tools for supporting city centers has long been underutilized. Digital tools can contribute to preserving and revitalizing city centers. Key questions are how digital tools can turn city centers into exciting places, which services should be offered, and how events can be communicated appropriately to attract residents and visitors alike. This paper reports the development of a city app that addresses the aforementioned challenges. Following the Agile Design Science Research Methodology (ADSRM), the elements and functions of the city app are evaluated using a survey and structural equation modeling (SEM). The results show that visiting intention and length of stay in the city center can be supported by such an app when attractive places and events are highlighted, and when location-based and profile-based interest functions are offered. Interestingly, gamification plays only a secondary role.

Keywords: Mobile App, Design Science, Structural Equation Modeling, Rural Area, Small Towns

4.1 Revitalizing the City Centers – Design and Evaluation of a City App

4.1.1 Introduction

City centers play a crucial role in vital cities and their functioning. They are essential for the supply of residents as well as visitors and provide meeting places for the citizens' social life (Bartelheimer et al., 2020, pp. 35–41). Particularly, the high street determines the city center's attractiveness, which is highly dependent on the shops, restaurants, and services offered (e.g., hair, beauty, and nail salons). Notwithstanding, city centers of small and mid-sized towns are exsanguinated (Deutsche Welle, 2022). The reasons are manifold. Big chain stores with their market power are driving small outlets out of business, shopping centers are built out of town, pulling spending capacity from the centers, and customers have changed their shopping behavior and often prefer to order via the Internet. All this gives retailers in the city centers a hard time, resulting in many close-downs (Deutscher Städte- und Gemeindebund, 2021). In Germany, 64,000 local retailers were said to be severely threatened until 2030 (IFH Köln, 2020a). But this was before the Covid-19 pandemic, which has fostered the decease. Now, the war in Ukraine, with exploding prices for energy and nearly any kind of products, accelerates this development even more.

The future development of the city centers depends on how the economic, political, and social situation will develop shortly (IFH Köln, 2022): First of all, the future of city centers is determined by the general economic development. This comprises the labor market, the savings rate, the procurement markets, the development of retail prices, as well as bankruptcies of suppliers or competitors. A primary factor for this is the further development of the Covid-19 pandemic. During the past years, people have saved much money and shown now pent-up demand. But the question is how people will spend their cash channel-wise and for what. Will they return to the city centers, or are they now used to online shopping and therefore lost for the stationary retail? If they return, the frequency and length of their stay will be crucial. The more often they return and the longer they will stay, the more they are prone to spend money directly in the city centers and support the local retailers. However, the war between Russia and Ukraine is a serious threat to this hope. The energy shortage already leads to high inflation rates while the people's income increases much slower. This reduces the customers' disposable income, so people

think twice before spending money on high street shopping, moving disposable money from consumer goods to electricity and heating. Lastly, also sustainability thoughts may impact future shopping behavior. Driving into the city centers, spending time there just for fun, and consuming goods may be questioned more and more.

It is mandatory for city centers to face this challenging situation and counteract the threatening processes of economic decline. Help may come from the same corner that bore some threats: digitalization. In many areas, digital solutions have successfully been employed to master threats and turn them into new opportunities. As customers of all demographic groups have quickly adopted digital offers via the Internet during the pandemic, digital tools may serve as a good starting point for city centers to take action and gain back customers. Hence, this paper aims to answer the following research question:

How can a digital tool like an app increase people's intention to visit and length of stay in the city centers?

This research question shall be answered with the help of a mobile app called the "City App." The goal of the app is to help city centers attract customers and make them stay there. The design and evaluation of this IT artifact are reported within this paper and followed the design science approach process (Hevner et al., 2004, pp. 75–105; Peffers et al., 2012, pp. 398–410), particularly the Agile Design Science Research Methodology (ADSRM) (Conboy et al., 2015, pp. 168–180). The ADSRM is an iterative process for conducting design science research in the IS context.

The remainder of this paper is organized as follows: In the next section, the related literature is reviewed to identify the research gap and further motivate the design of the app. As our search for other artifacts will show, a new solution is needed to solve the problems of city centers described above, particularly in rural regions. An analysis of the studies results in information about what factors make cities vital and the needs and expectations of customers. In section 3, the design methodology is explained in more detail, followed by a description of the artifact. Section 4 presents the evaluation of the artifact. In line with previous studies (Liu et al., 2014, pp. 34–43; Trochidis et al., 2006, pp. 234–243), we employ a value-co-creation process incorporating end customers into

the design of the City App. Hence, citizens are asked about the artifact with the help of a quantitative survey. The paper closes with a discussion of the results, implications, and limitations of our research.

4.1.2 Literature Research

Research on citizen-centric applications (apps) that aim at supporting city centers and improving their attractiveness is scarce. Of the twelve papers found (see Table 14 for a summary), two focus on citizen participation: Billert and Peters (2019, pp. 172–189), as well as SUH (2021, pp. 11–20), develop a platform where citizens can communicate about solutions for problems in their city and hence participate in the decision-making process. On the platform of Billert and Peters (2019, pp. 172–189), citizens can additionally develop their own ideas and create mock-ups or elevator pitches.

Six papers focus on the development of smart services. However, most of these papers do not develop real solutions but methods, processes, or requirements for service design and development. Hosseini et al. (2018, pp. 243–257) is the only paper addressing how digital innovations can be brought to rural areas. For this, they outline an innovation process blueprint. Liu et al. (2014, pp. 34–43), as well as Meriläinen et al. (2022, p. 37), developed new design methods for smart citizen services. While Liu et al. (2014, pp. 34–43) focus on integrating live events and values, which are actions that need to be executed to fulfill a citizen's request, Meriläinen et al. (2022, p. 37) focus on sustainability and postulate design principles for developing such sustainable services. Gnewuch et al. (2017, pp. 1–13) and Wiethof et al. (2022) focus on conversational agents for customer service. Gnewuch et al. (2017, pp. 1–13) derived a set of meta-requirements and design principles for cooperative and social conversational agents, while Wiethof et al. (2022) concentrated on the design principles of conversational agents and evaluated a conversational agent prototype. Meyer et al. (2018, pp. 291–300) investigated the human-to-computer relationship in general and analyzed the impact of different combinations of technology-mediated value services in retail customer relationships in detail.
Anthony Jnr et al. (2020, pp. 1023–1047) propose a big-data-driven multi-tier architecture for Mobility-as-a-Service in smart cities. Mramba et al. (2016, pp. 121–133) investigated the special case of street traders in rural African areas. They looked at the barriers that street traders face and propose technological innovations to address these problems. Tang

et al. (2017, pp. 881–897) developed a decision support system for novice e-buyers that supports them in their purchase decisions.

Our paper is most related to the one of Bartelheimer et al. (2018), who created a multi-sided community platform for local high-street retail. This platform concentrates on the community aspect and provides a set of IT artifacts to support small and medium-sized retailers in leveraging their competitive position.

In sum, there is a lack of technical solutions that shall support city centers in their efforts to reconquer visitors. Most papers either focus on methods, requirements and architectural objectives or concentrate mainly on e-buyers. Further, if artifacts are developed, they are usually evaluated only qualitatively. In contrast, this paper introduces a practical implementation assessed quantitatively with structural equation modeling.

Table 14. *Review of Urban Digitalization Literature*

Reference	Objective	Kernel Theories	Method	Findings
Anthony Jnr *et al.*, 2020	Big Data Driven Multi-Tier Architecture for Electric Mobility as a Service (eMaas) in Smart Cities	DSRM, Socio-technical Systems (STS), Actor Network Theory (ANT), Layer Architecture of Digital Technology	Case Study, interview with four Maas experts	A multi-tier architecture to support the collection, processing, analytics, and usage of mobility data within smart cities.
Bartelheimer et al., 2018	Designing multi-sided Community Platforms for Local High Street Retail	DSRM	Evaluation of smartmarket against rival artifacts, prototype evaluation	A new class of IT artifacts and smartmarket; a platform to leverage the competitive position of small and medium-sized retailers.
Billert & Peters, 2019	Collaborative Development of a citizen-initiated Service Development Gateway	DSRM, Collaboration Engineering	Requirements Workshop, SWOT-Analysis	"Digitalisierungsstraße" Prototype
Gnewuch et al., 2017	Designing Cooperative and Social Conversational Agents for Customer Service	DSRM	Theory-based	A set of meta-requirements and design principles.
Hosseini et al., 2018	How to Bring Customized	DSRM	A case study in a small	How to bring digital innovation to rural

	Digital Innovation to Rural Areas		town in southern Germany	areas, smart towns, and an innovation process blueprint.
Liu *et al.*, 2014	Designing citizen-centric services in smart cities on a scenario-based design. The Shèjì Zhìhuì Shìmín Fúwù method.	Service blueprinting, value co-creation, and universal values.	Theory-based	The design of citizen-centric services requires values. A bottom-up approach leads to the service design. Life events allow a theoretically robust development.
Meriläinen et al., 2022	Developing Smart Sustainable City (SSC) Services: Towards Actor Engagement Approach	DSRM	Semi-structured interviews with smart city experts	Actor Engagement Approach and three design principles for developing SSC.
Meyer et al., 2018	Can Customer Value Services enhance the Experience?	DSRM	Human-to-computer-relationships	The impact of different combinations of technology-mediated value services in customer-retail relationships
Mramba et al., 2016	Technology for street traders in Tanzania	DSRM	A qualitative study of 285 street traders analyzed with mixed methods	Barriers for street traders in Dar es Salaam and technology innovations to address the daily challenges.
SUH, 2021	Designing a citizen participation system	Design Thinking, DSRM	Case Study with 20 Citizens and Design Workshops	Smart citizens experience space, which utilizes space as a tool to visualize space-based information and multi-faceted stimulus events.
Tang *et al.*, 2017	Consumer decision support system (CDSS) for novice buyers	DSRM	User study in a simulated scenario	A needs-based CDSS for novice buyers aids e-buyers in making purchase decisions.
Wiethof et al., 2022	Design and Evaluation of an Employee-Facing Conversational Agent (CA) in Online Customer Service	DSRM	Evaluation of a CA prototype with 21 users	A set of design principles for Hybrid Intelligence Systems.

4.1.3 Methodology

This paper reports the design and evaluation of an application, called City App, which aims at helping city centers in their efforts to attract more visitors and increase their stay in the city center. The design science approach is appropriate for designing such an IT artifact (Hevner et al., 2004, pp. 75–105; Peffers et al., 2012, pp. 398–410). More precisely, we followed the Agile Design Science Research Methodology (ADSRM) introduced by (Conboy et al., 2015, pp. 168–180). The ADSRM process consists of seven consecutive phases, which are passed through iteratively. See Figure 8 for the complete ADSRM process.

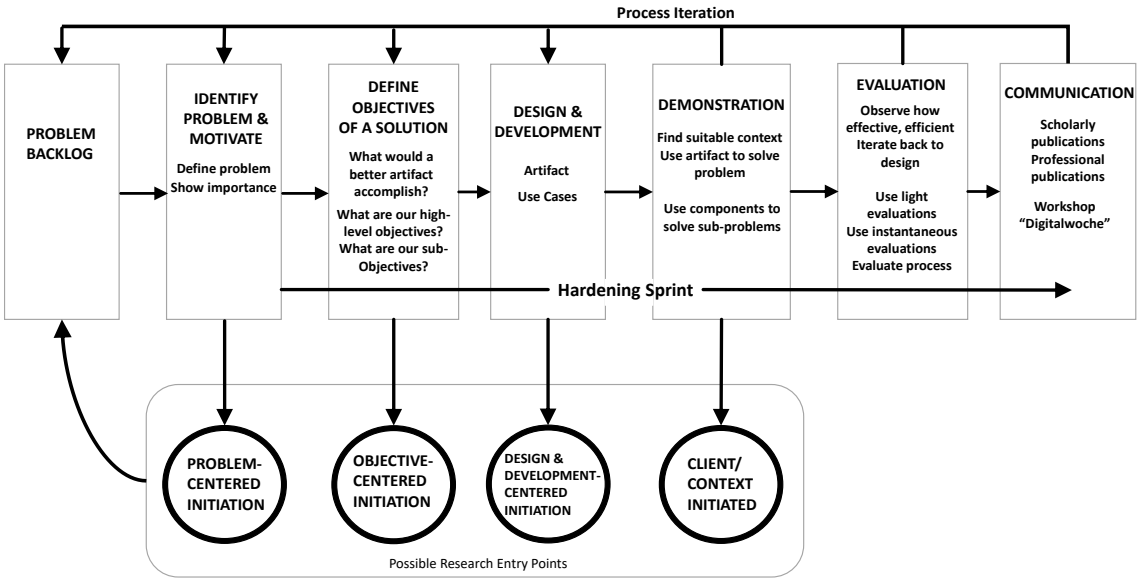


Figure 8. *Agile Design Research Methodology – City App Study* (ADSRM Framework) (Conboy et al., 2015, pp. 168–180)

The City App Design Process

Phase 1 & 2: Problem Backlog & Problem Identification and Motivation.

As described in the first section, city centers suffer from a decline of visitors, particularly in rural regions. Many customers have been lost to e-commerce and are now estranged from going into the city centers. The literature research has shown that few solutions exist for city centers. Additionally, they hardly go beyond communities (Bartelheimer et al., 2018), conversational agents (Gnewuch et al., 2017, pp. 1–13; Wiethof et al., 2022), or focus on very special problems (Mramba et al., 2016, pp. 121–133). Hence, a novel solution is required that incorporates the functions needed to attract customers and make them stay in the cities.

Phase 3: Definition of the Solution's Objectives.

Previous studies suggest sustainability principles for the design of smart city services (Meriläinen et al., 2022, p. 37), which are said to increase the sustainability of a town. Yet, it is crucial that the services offered reflect the needs of the citizens and prospective customers. Otherwise, those services will not be used, and the sustainability aspect will not kick in.

Several studies investigated which factors make city centers vital (IFH Köln, 2016, 2018, 2022). The results show that vital cities dispose of a variety of different offers like nice places to be visited (e.g., parks, buildings), eclectic and exciting events, and last but not least, a diversified service offer in terms of shops, gastronomy, etc.

The City App should support this and give (prospective) visitors of the city center information about these factors. While this information can enhance people's intention to visit the city center, it does not necessarily prolong their length of stay. To achieve this, additional functions need to be provided that are suitable to hold.

Phase 4: Design & Development.

IT artifacts in the field of retail and city centers can be categorized into three classes which are not necessarily mutually exclusive (Bartelheimer et al., 2018): (1) White label solutions, (2) Online communities, and (3) Mobile shopping companion apps.

The City App falls into categories 1 and 3 as it is configurable, and the content can be adapted to a specific city on the one hand. On the other hand, it provides services that complement and extend retailers' services and connect the physical service landscape with the digital presence.

The app addresses three stakeholders: the city with its citizens and visitors, as well as the town's retailers. Hence, the stakeholders fall into three groups: municipal (such as city marketing and city administration), commercial (shops, hotels, restaurants, doctors, craftsmen/craftswomen), and private (citizens, visitors, or groups such as clubs in the city)

As the City App aims to attract prospective customers and make them stay in the city, it is not intended to be provided by single retailers but by the town itself. Hence, the municipal actors are the number one stakeholders intended to operate as the product owners and process all information.

The development of the City App is based on the best practices and methods suggested in the extant literature. In addition, customers have been integrated into a value-co-creation process to meet their expectations and needs (Liu et al., 2014, pp. 34–43). Following the ADSRM framework, the design & development has undergone three cycles. In the first cycle, the three identified main features, *places*, *events*, and *services* (IFH Köln, 2016, 2018, 2022), have been integrated into the artifact. The first feature, "places", offers information about places to visit, such as sights and recommendations for popular spots. As live events have been proven to contribute to the vitality of cities (Liu et al., 2014, pp. 34–43), the second feature, "events", has been added to display cultural, local, or municipal events. The third feature, "services", shows interesting shops, gastronomy or hotel offers, medical services, and links to local craftsmen. With the first iteration, the City App provides features to attract customers and make their preparation for their stay and the stay itself in the city easier and more convenient. In the second stage, real-time life information is added, which is highly important for the stay (SUH, 2021, pp. 11–20). Hence, the "Around Me" function provides location-enabled services. For this, the user's GPS position is used to select and display coupons, friends, or events close to the user's location. In the third iteration, the behavior of users is analyzed and used to track the user's interests and predict personal preferences, like in Anthony Jnr et al. (2020, pp. 1023–1047). Therefore, the service "Personal Offers" is added. This function provides unique offers to the user based on the usage history, like visited places, events, and services used. Figure 9 displays the prototype's three iterations that have been realized as an Android app.

Phase 5 & 6: Demonstration & Evaluation.

The City App prototype has been evaluated with an ex-ante evaluation (formative) by literature research and an ex-post with a summative assessment by citizens. For the latter, a questionnaire was developed with a structural equation modeling approach to be applied.

Phase 7: Communication.

The City App has been presented to city managers and shop owners in a proof-of-concept demonstration to demonstrate its feasibility and identify its potential shortcomings. This demonstration helped to inform the stakeholders about the potential of digital tools in general and the City app in particular. The app has been considered valuable during this event in a small city in a rural region.

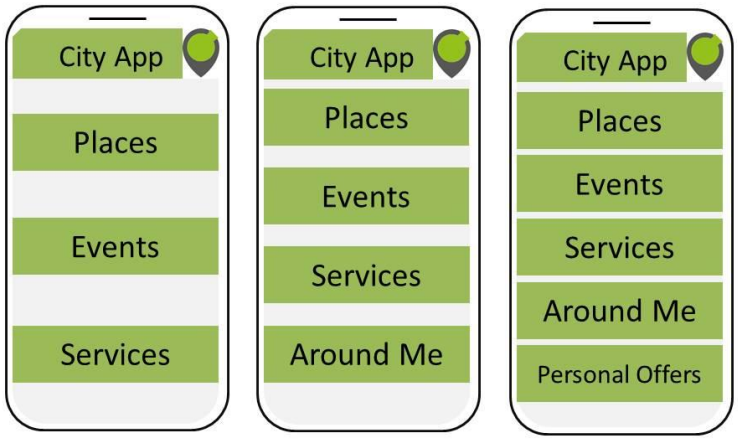


Figure 9. *Three Stages of the City App Prototype*

4.1.4 Evaluation

Research Model

In comparison to the classic adoption theory (e.g., Davis, 1989, pp. 319–340; Venkatesh et al., 2003, pp. 425–478), the usage intention of people concerning the City App is not in focus. Instead, it is of interest to what degree the app fosters the intention of people to visit the city center and prolongs their length of stay. Hence, we use the "Contribution of the City App on Visiting Intention and Length of Stay" as the dependent variable. The construct Contribution captures the perceived behavioral impact of the City App on city center visits. It therefore combines indicators related to visiting intention and expected length of stay. Similar to the Technology Acceptance Model (TAM)(Davis, 1989, pp. 319–340), the functions provided by the app play a crucial role in the visiting intention. If the functions are regarded as useful, the more likely it is that people visit the city centers. In turn, the app's usability is an antecedent for the perceived usefulness. If a tool is cumbersome, its usefulness suffers. In this context, usability reflects the perceived quality of user interaction with the application, including the general ease of use, the clarity of interaction flows, and the overall user experience.

For several years, gamification elements have been used to make tools more interesting, such that users get into the flow (Nakamura & Csikszentmihalyi, 2009). The primary purpose of gamification is to make users do things more often and longer (Hamari et al., 2015, p. 15; Seaborn & Fels, 2015, pp. 14–31). We, therefore, decided to investigate the impact of gamification on the perception of the usefulness of the City App. Hence, we hypothesize:

H1: The more the City App functions are regarded as useful, the more the app will attract customers to the city center and the longer their stay will be.

H2: The more usable the City App is regarded, the more the app will be considered as useful.

H3: The more gamification elements are appreciated within the City App, the more the City App is regarded as useful.

Previous studies investigated the importance of different characteristics on the vitality of city centers (IFH Köln, 2016, 2018, 2022). According to this, the facilities of the cities play a crucial role in people coming into the centers and staying there. In particular, only when the town's facilities are attractive the according functions provided by the app can be regarded as useful. Hence, we hypothesize:

H4: The more the city's facilities are regarded as attractive, the more the City App is regarded as useful.

The resulting research model is depicted in Figure 10, together with the results.

Data Collection and Descriptive Analysis

The survey was distributed online and supplemented with a paper-based version. In total, 109 online distributed questionnaires were answered. 43 (39.4%) responders were male, and 65 (59.6%) were female. One person did not want to state the gender. On average, our participants were 30.25 years old, and most respondents were between twenty and thirty years old. 53.2% of our participants had a high school diploma, and a further 35.8% of them had an academic degree, while only 8.3% had a secondary school certificate (3% of others). A 5-Point Likert response scale was used, in which responders specify their level of agreement to a statement in five points: (1) Strongly disagree, (2) Disagree, (3)

Neither agree nor disagree, (4) Agree, (5) Strongly agree. Before answering the questionnaire, participants were introduced to the City App prototype and its core functionalities (places, events, navigation, and personalized offers) through a short presentation and illustrative screenshots. This ensured that respondents had a concrete understanding of the application when evaluating its potential impact.

City and online shoppers were equally distributed (44.9% preferred to shop locally, 26% were indecisive, and 28.4% chose to shop online). Most responders visit the city to go shopping (80.7%) or use the gastronomical offer (76.1%). Visiting the city center for sightseeing (81.7% disagree) or because of the leisure or cultural offers is not likely (56.9% disagree). Most of the respondents visited the city during the opening times of the stores, and 64.2% disagreed with visiting the town for window shopping. Using offered services in the city is proportionately distributed; almost half agree, e.g., visiting a hairdresser (47.7 agree, 52.3% disagree) or a doctor (44% agree, 56% disagree) in the city center.

Most respondents (60.6%) visit the city at least weekly by bike, followed by public transport (57.8%), by car (51.4%), and by foot (48.1%). Interestingly, more than one-third (37.6%) state that they do not visit the inner city by car. Slightly more than an eighth (13.6%) state they visit the city rather than weekly, no matter which mode of transport they use. More than half (57.8%) of the respondents stayed one to two hours in the inner city, while 18.3% less than one hour and 23.9% more than two hours.

Table 15 displays the different assessment areas. The results count for an inner city, and every respondent rated their city. The only constraint was that the city had to be rural. For city facilities, gastronomy was most important, followed by the range of goods and the retail offer in the town. The ambiance had the highest standard deviation and seemed to be either essential or not crucial to the city visitors. The same can be concluded for leisure facilities.

The second area of assessment focuses on the functional elements of the City App. Users particularly value information about places, sights, and events, and they also prefer navigation features. Event information received particularly high agreement ($M = 4.52$). Rather than indicating a measurement problem, this strong approval likely reflects the

central role of events as an attraction factor for visits to city centers. In urban contexts, events function as coordination points that connect visitors with places, services, and social activities. The high mean value therefore reflects the perceived relevance of this function within the City App. At the same time, the item still exhibits sufficient variance and thus continues to contribute meaningfully to the measurement of the construct. Further, users prefer navigation features. They are interested in coupons, but the standard deviation, if they want the vouchers to be personalized according to their interests, was high, so it can be assumed that this function will be used only by specific users. For the further development of the app, the third area of interest dealt with gamification and usability elements. App users seem not interested in gamification, and the usability of our app was rated as mediocre.

The final area of interest was the self-assessment of how the app could contribute to the visiting intention and the length of stay for the city centers. The results show an ambiguous picture. The app might influence these factors more indirectly. At the same time, the standard deviation was high, so it also depends on the respondent if they are affected to visit the city center more often or for a more extended period.

Analysis

In addition to the descriptive analysis, the empirical data was also analyzed concerning causal relationships with the help of IBM SPSS Statistics 27 and Smart PLS 4.0 (Ringle et al., 2022). Partial Least Squares (PLS) is a non-parametric method suitable for smaller sets like the one this paper deals with. Bootstrapping was done with 5,000 samples to determine the significance of weights, loadings, and path coefficients (Hair et al., 2017). There were no missing values, and the program was set to 300 maximum iterations, with a stop criterion of 7. The structural equation model (SEM) consists of two elements: the measurement model, which specifies the relationship between the constructs and their indicators, and the structural model, in which the relationships between the constructs are analyzed (Chin & Newsted, 1999, pp. 307–341; Henseler et al., 2009, pp. 332–344). The PLS-SEM approach was chosen over a covariance-based analysis because our exploratory research question has proven power in explaining complex behavior research (Lowry & Gaskin, 2014, pp. 123–146).

Assessing the measurement model. We used a reflective measurement model and evaluated four criteria: internal consistency reliability (ICR), indicator reliability (IR), convergent validity (CV), and discriminant validity (DV). The constructs were operationalized using multiple reflective indicators. City Facilities was measured with five indicators capturing central aspects of urban attractiveness, such as leisure facilities, retail offer, gastronomy, and ambiance. Although these indicators represent different characteristics of the city center, they jointly reflect the perceived attractiveness of the urban environment. The empirical results support this operationalization: all indicators contribute significantly to the construct and the variance inflation factors remain well below critical thresholds, indicating that the indicators capture complementary rather than redundant aspects of city center attractiveness (see Table 15). City App Functions comprises several functional elements of the application, including information about places and events, navigation services, and personalized offers, which together represent the core informational and service-related capabilities of the City App. These indicators correspond to the functional City App assessment reported in Table 15 and represent the perceived usefulness of the core application features. Gamification and usability were each measured with three indicators reflecting typical interaction and design elements of mobile applications. Finally, the construct Contribution captures the expected behavioral effects of the City App and is measured through indicators related to visiting intention and length of stay. For the ICR, Cronbach's Alpha (CA) exceeds 0.70, and the composite reliability (CR) exceeds 0.8, indicating solid reliability (Nunnally & Bernstein, 1994). For the CR, the Average Variance Extracted (AVE) values exceed 0.50. The Fornell-Larcker criterion (FLC) and the cross-loadings need to be checked for the DV. The FLC states that the AVE of each latent variable should be greater than the latent variable's highest square correlation with any other latent variable (Fornell & Larcker, 1981, pp. 46–48). Furthermore, the cross-loadings ensure that the models' constructs differ sufficiently from each other if each indicator loads the highest with its items (Chin, 1998, pp. 295–336).

Assessing the structural model. The Variance Inflation Factor (VIF) is an indicator of collinearity. As shown in Table 15, most of our VIFs did not exceed the maximum level of 10 (Diamantopoulos & Winklhofer, 2001, pp. 269–277) and only some the threshold of 5 (Henseler et al., 2015, pp. 115–135). The assessment results for the significance and relevance of the structural model relationships are shown in Figure 10. Only the path

coefficient between Gamification and City App Functions was not significant, so that H3 could not be confirmed. H1, H2, and H4 could be confirmed with medium (H1, H2) to small (H4) effect sizes f^2. Finally, the Q^2 values for the endogenous constructs were over 0 ($VI1_{Q2}$ = 0.349, $VI2_{Q2}$ = 0.353, $LS1_{Q2}$ = 0.357, $LS2_{Q2}$ = 0.318). Hence, predictive relevance was established (Hair et al., 2014, pp. 106–121).

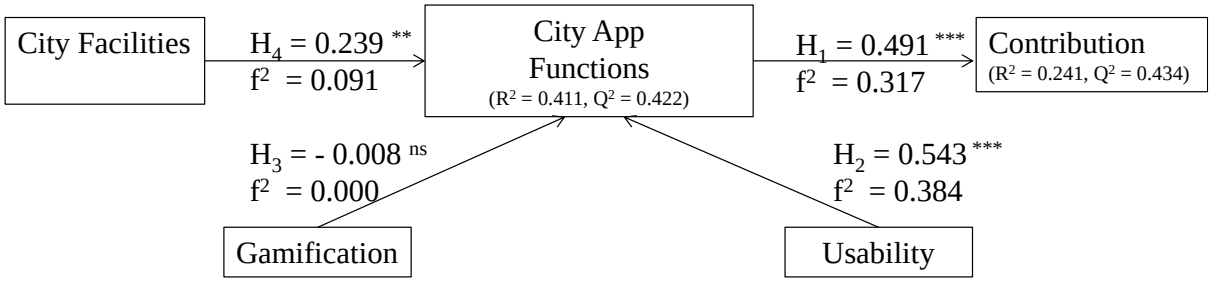


Figure 10. *Structural Model Results – City App Study*

Table 15. *Descriptive Statistics – Urban Survey Data*

Construct	Items	Questionnaire Item Focus	Mean	Standard Deviation	Weights		Variance Inflation Factor
Information about the City							
City Facilities	CF1	Leisure Facilities	3.37	1.033	0.214	***	1.926
	CF2	Range of goods	3.71	0.890	0.245	***	2.342
	CF3	Ambiance	3.58	1.057	0.316	***	1.680
	CF4	Gastronomy	3.86	0.907	0.273	***	2.444
	CF5	Retail offered	3.61	0.895	0.198	*	1.840
City App (Functional Assessment)							
Places	CP1	Information about Places	4.32	0.804	0.299	***	1.840
	CP2	Information about Sights	4.34	0.830	0.231	***	1.582
Events	EV1	Information about Events	4.52	0.702	0.237	***	1.575
Around me	AM1=2	Navigation around me	4.37	0.846	0.254	***	1.926
Personal Offers	PO1	Personal Coupons	3.35	1.279	0.342	***	1.186
City App Gamification and Usability Elements							
Gamification	GA1	Points/Awards	2.29	1.257	0.388	***	2.294
	GA2	Rankings	2.06	1.088	0.339	***	2.083
	GA3	Quests	2.05	1.187	0.417	***	1.854
Usability	US1	Generally	3.47	0.958	0.400	***	3.348
	US2	User flow	3.42	0.946	0.384	***	3.275
	US3	Fun	3.26	1.062	0.319	***	2.046
Contribution of the City App on Visiting Intention and Length of Stay							
Visiting Intention	VI1	Increasement by App use	2.72	1.306	0.282	***	4.758
	VI2	Likeliness by App use	2.54	1.214	0.294	***	5.185
Length of Stay	LS1	Increasement by App use	2.72	1.261	0.278	***	5.653
	LS2	Likeliness by App use	2.61	1.210	0.266	***	5.993
Significance of indicators: ns=not significant, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$							

4.1.5 Discussion

Summary

In this paper, we reported the design and implementation of a City App that aims at helping city centers in attracting more customers and prolonging their stay. As our literature review has shown, there is no appropriate tool for city centers encompassing several supporting features, so that a new app was developed following the ADSRM. The app's functions have been created and added in several development iterations.

Based on literature research, the main functions of providing information about exiting places in the city, events that will take place, and services offered in the town have been integrated with the first step. These features provide helpful information to all people who are not in the city center but intend to go there. In order to entrap visitors to stay longer in the city, two additional features were added in the successive two iterations. Based on the position of visitors, location-enabled services are provided, like sales coupons for shops nearby, friends, or events in proximity. Lastly, the usage behavior is analyzed concerning visited places, events, or services used. Based on this history, recommendations are given when users are in the city.

Results

To answer our research question, "*How can a digital tool like an app increase people's visiting intention and length of stay in the city centers?*" a survey was carried out among visitors of city centers and online users. The results show that the higher the app's functions are valued, the more likely users will visit the city center and stay longer. Among the app features, personal coupons are of the least but still positive interest. Particularly, information about events is of the highest interest to users, closely followed by geo-location-based information and information about places. The perception of the app features by users depends on two factors. First, the app usability exerts a high impact. This is not surprising as for many years now, usability has been a must and serves as a gatekeeper. IT artifacts can be as helpful as possible. If they lack usability, they will hardly be used. Secondly, the city's situation also plays a role, particularly the offers that can be found in the city center. However, the influence of the city facilities is much weaker than the one of the app usability.

Interestingly, gamification elements do not influence the perception of the app's usefulness. It seems people are not interested in being additionally entertained by the app. The app functions are valuable enough for them.

However, it has to be considered that the model's explanatory power is medium. That means that there are still other factors that influence people's intention to visit the city center and to stay there as well as their perception of the app features.

Implications

This paper demonstrates that technical solutions such as the City App can support the attractiveness of city centers by positively influencing visitors' intention to visit and their expected length of stay. While the offerings of the city center for sure play a role in people's decision to visit the center, this factor should not be overestimated. The relation is visible, but the impact is low. Although the attractiveness of a city's center should not be neglected and should be included in urban development plans, it is more important to "sell" the available offer of a city center well. A City App can serve as a vehicle to do this. The more information about the city is provided and the better this information is presented, the more people are stimulated to visit the city center and stay.

Enriching the app with gamification elements is not essential in this connection. Such features are rated low and have no impact on the perception of the app. So instead of spending time and effort on wrapping the information in sweet candy in the form of gamification elements, decision-makers are well advised to concentrate on the content provided to users and the usability. Creating tools of high usability is not easy as it sounds. Before Apple introduced the easy-to-use iPhone and iPad with highly usable interfaces, usability was often a stepchild of development. However, this has entirely changed since then. Nowadays, usability determines to a great extent if a tool is assessed as useful. Hence, city developers should focus on usability and the provided content.

With regard to the offered content, dynamic information about events and geo-location-based information is of the highest interest to users. Certainly, static information about places is the basis for that. But, personalized offers are much less critical to the general audience. Only a subset of people is really interested in such offers. For this, it would be

better to identify interested users with the help of modern data analytics methods and spend the money more precisely.

4.1.6 Limitations and Future Research Directions

As always, also this paper is not without limitations. As mentioned, the explanatory power of the research model is medium. A reason may be that the sample was relatively small. But presumably, other influencing factors have not been investigated, like the community perspective. Future research should incorporate these aspects into the app and analyze their impact. Concerning the community perspective, social norms will most probably come into effect.

Also, we analyzed the visiting intentions of people and did not observe if app usage impacts the actual visits and lengths of stay. This should be investigated in a field experiment where the app is introduced in a city, and people can use the app. Tracking app usage and city center visits can shed light on the genuine causal relationship.

4.1.7 Visualizing the Design Logic: Processes, Entities, and Relationships

This complementary section extends the original publication by explicitly formalizing the internal design logic of the City App. While the main article evaluated user outcomes and revitalization effects, the present section focuses on the architectural and processual structure underlying the digital artifact.

In line with Agile Design Science Research (Gregor & Hevner, 2013, pp. 337–355; Hevner et al., 2004, pp. 75–105), digital artifacts must be understood not only through their observable functionalities but also through their underlying data structures and process logics. The City App operates as a socio-technical system in which urban content, stakeholder roles, and interaction processes are systematically organized through a defined information architecture.

To enhance conceptual clarity, two modeling perspectives are introduced:

- An Entity-Relationship Diagram (ERD) representing the structural data architecture
- Event-Driven Process Chains (EPCs) modeling the dynamic interaction logic

Together, these visualizations formalize how urban information is created, structured, and delivered within the app-based infrastructure.

Entity-Relationship Diagram: Structural Architecture

The ERD shown in Figure 11 represents the logical data model of the City App. It visualizes the core entities, their attributes, and the cardinalities governing content creation and user interaction. The diagram was developed using Lucidchart as a conceptual modeling tool in order to ensure clarity of entity definitions, relationship types, and multiplicities. While the ERD does not represent an implementation-level database schema, it formalizes the conceptual data model underlying the digital artifact.

The structural backbone of the City App consists of five primary entity domains:

1. User (individual visitors interacting with the app)
2. Place (geo-referenced urban locations)
3. Event (time-bound activities linked to places)
4. Offers (location-based commercial incentives)
5. ContentProvider (urban stakeholders managing content)

The conceptual model focuses on a limited set of object types representing the core information elements required for the City App. As the artifact is designed as a lightweight urban information system rather than a comprehensive smart city platform, only entities directly involved in user interaction and content provision are modeled. Additional urban entities such as categories of urban content or organizational providers could be incorporated in extended versions of the system but are not required within the conceptual scope of the present artifact. This abstraction follows the principle of conceptual parsimony and reflects the problem-oriented nature of design science artifacts (Gregor & Hevner, 2013, pp. 337–355; Hevner et al., 2004, pp. 75–105).

As illustrated in Figure 11, these entities are relationally connected through cardinalities:

- Events and Offers are linked to exactly one Place
- ContentProviders create Events and Offers
- Users interact with Places, Events, and Offers via associative entities
- LocationContext dynamically determines spatial proximity
- InteractionLog captures behavioral traces for evaluation purposes

The ERD therefore demonstrates how physical urban structures (places, events, offers) are translated into relational database logic. Urban space is not merely digitized; it is reorganized into a structured information system with defined cardinalities and interaction pathways.

From a socio-material perspective, the ERD demonstrates how digital infrastructure reconfigures urban space into an operational data model. Physical locations become database entities, urban events become temporally bound objects, and user behavior becomes loggable interaction events. This translation of urbanity into structured relational logic constitutes the backbone of the digital artifact.

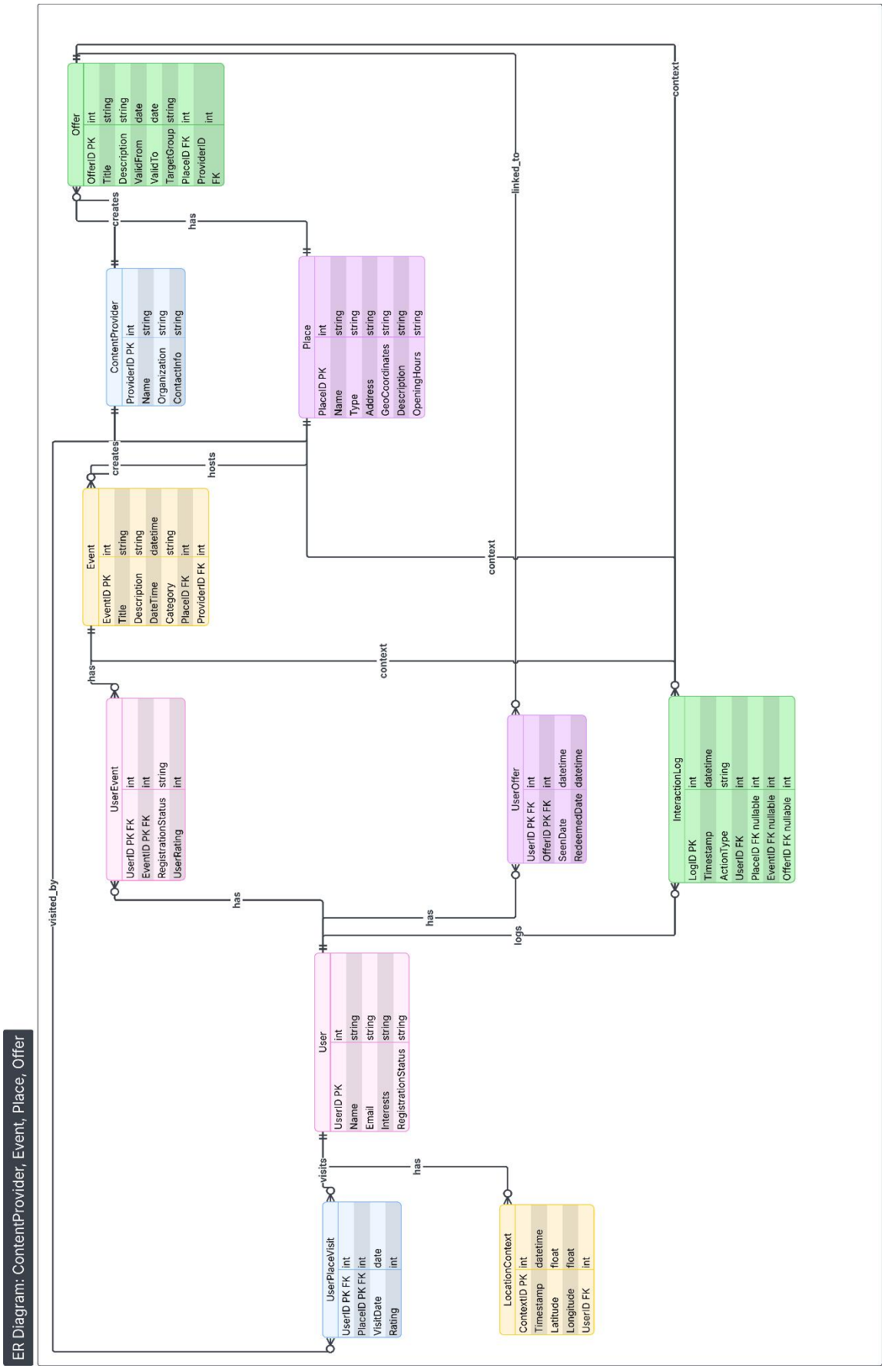


Figure 11. *Entity-Relationship Diagram (ERD) of the City App*

Event-Driven Process Chains: Interaction Logic

While the ERD captures static structure, it does not explain how actors navigate through the system. To model dynamic behavior, Event-Driven Process Chains (EPCs) were developed and are presented in Figure 12. The EPC diagrams were likewise modeled using Lucidchart to formalize event-function sequences and decision logic in a structured and transparent manner. Two complementary interaction perspectives are arranged side by side and visualized: The visitor-side interaction flow (left) and the provider-side content management flow (right). This parallel visualization highlights the dual logic of the artifact: user engagement and content governance. In the EPC notation used, events (E) represent system states, while functions (F) denote executable activities.

The visitor-side EPC models the visitor journey from app launch to contextual content interaction. The process begins when a user is physically present in the city center and launches the app. The system detects the user's location and retrieves contextually relevant content (Places, Events, Offers). Once content becomes visible, the user may either exit the app or select a specific item. If an item is selected, the process continues with viewing details, navigating, saving, or interacting. Each interaction triggers logging mechanisms, resulting in stored interaction data within the system. The EPC makes explicit that user interaction follows an event-driven logic rather than a purely navigational structure. Content visibility depends on contextual triggers and predefined data relationships specified in the ERD (Figure 11).

The provider-side EPC models the backend workflow of content providers. After authentication, providers choose a content type (Event or Offer). Depending on this decision, different process paths are activated. Providers enter content data, which is subsequently validated by the system. Upon successful validation, the content is published and becomes visible within the app interface. This process illustrates decentralized but structured governance. The backend workflow ensures that local stakeholders can manage digital urban representation without direct technical intervention in the system architecture.

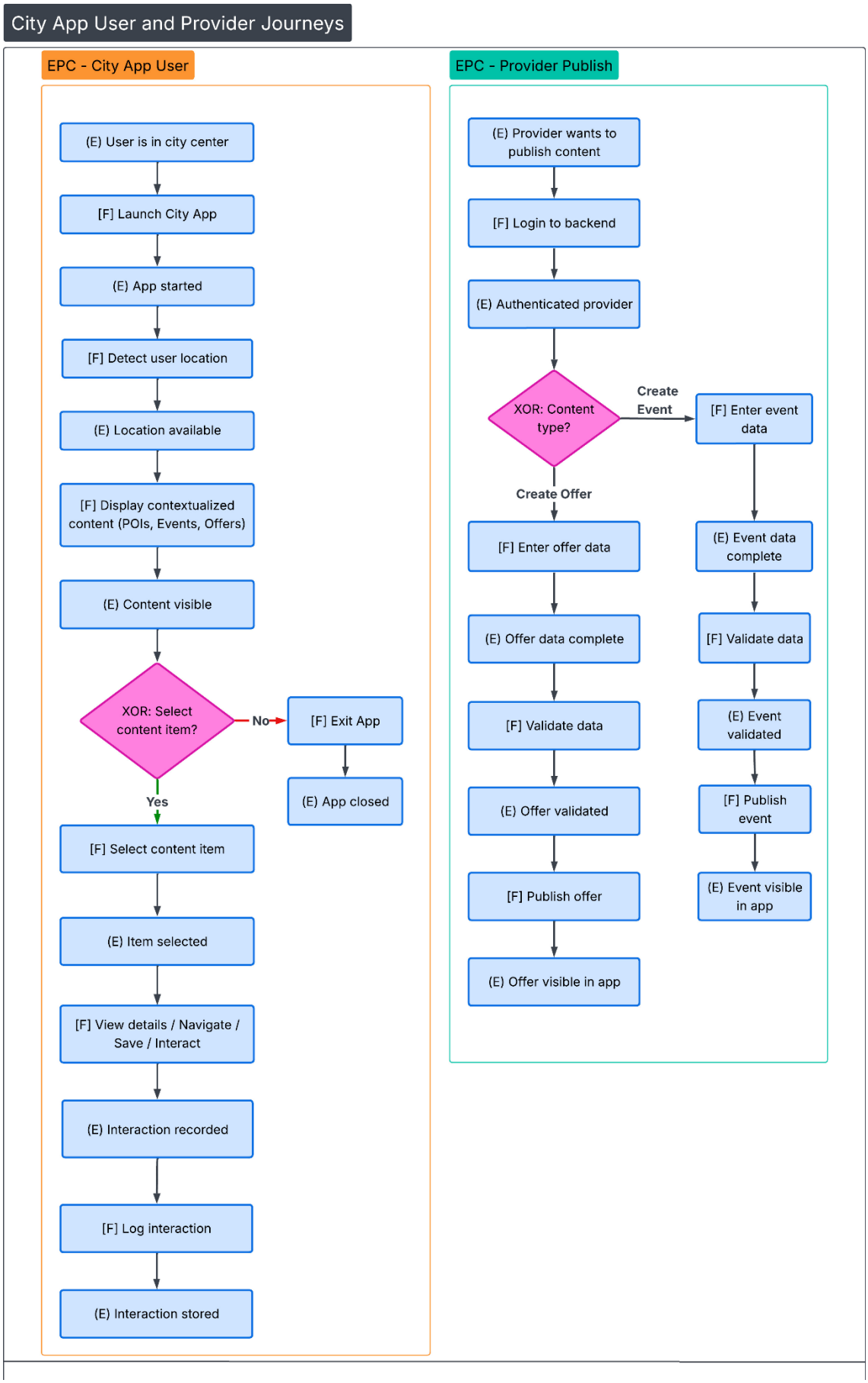


Figure 12. *Event-Driven Process Chains (EPC) of User and Provider Interactions*

Design Science Reflection

From a Design Science perspective, the modeling exercise demonstrates that the City App constitutes more than a functional interface. It is a structured artifact integrating:

- formal data architecture (ERD)
- process transparency (EPC)
- stakeholder-oriented usability

The ERD ensures structural consistency and scalability. The EPCs make implicit interaction assumptions explicit and allow validation with both technical and non-technical stakeholders.

Crucially, the visualization reveals that digital urban revitalization does not emerge automatically from frontend features. It depends on coherent backend design and structured information governance. Digitalization here operates as a structuring layer of urban coordination, reorganizing how actors, spaces, and events are represented and connected within a hybrid urban system.

Paper 5: **Enhancing Urban Attractiveness through Digital Integration: Multivariate Insights from Mid-Sized Cities**

Authors: Christina Gross, Richard Lackes

Abstract: This paper analyzes how digital elements relate to the perceived attractiveness of city centers in medium-sized German cities undergoing structural change. Against the backdrop of retail transformation and evolving patterns of urban use, the study draws on harmonized survey data collected between 2014 and 2018 across multiple cities. Combining principal component analysis (PCA) with city-specific regression models, it examines the structural composition of urban perception and the relative influence of spatial quality, commercial infrastructure, and digital interaction. The results show that physical and functional qualities, such as safety, cleanliness, and the coherence of retail and public space, remain the dominant predictors of perceived urban attractiveness. Digital interaction, while increasingly embedded in urban environments, does not exhibit independent explanatory power in shaping overall attractiveness evaluations. Rather than redefining urban perception, digital elements operate as a supplementary layer that mediates experience without structurally replacing material qualities. By empirically situating digital transformation within the broader structure of urban perception, the study contributes to debates on hybrid urbanism and provides a data-driven perspective on digitalization in medium-sized cities.

Keywords: urban attractiveness; digital integration; digital transformation; smart cities; hybrid urbanism; urban perception; principal component analysis

4.2 A Data-Driven Structural Analysis of Perceived Urban Attractiveness under Digital Transformation

4.2.1 Introduction and Positioning

Urban attractiveness has long been considered a central factor in city development, retail vitality, and spatial competitiveness (Carmona, 2021; Montgomery, 1998, pp. 93–116). Classical urban theory emphasizes spatial quality, safety, legibility, and functional diversity as key determinants of positive place perception (Gehl, 2011). In parallel, research on urban economics highlights the role of retail structure and experiential consumption in sustaining inner-city vitality (Gospodini, 2002, pp. 59–73; Zukin, 1998, pp. 825–839).

At the same time, many European city centers are facing mounting structural pressures resulting from demographic change, shifting consumption patterns, and the expansion of e-commerce (European Commission, 2021; OECD, 2021). Increasing retail vacancies and declining footfall have intensified debates about the long-term viability of traditional inner-city formats (IFH Köln, 2020b).

Against this backdrop, digital transformation has fundamentally altered the conditions under which urban spaces are perceived and used. The diffusion of smartphones, platform economies, and digitally mediated information flows, alongside broader societal and behavioral shifts, has reshaped how citizens navigate, evaluate, and interact with city centers (Kitchin, 2014a; Townsend, 2013). Urban environments are no longer purely physical entities; they operate as hybrid socio-technical systems in which digital infrastructures, such as urban information systems, intersect with material space.

This development has led to the notion of the “hybrid city,” in which physical and digital layers co-exist and co-produce urban experience (De Souza e Silva, 2006, pp. 261–278; Kitchin, 2014b, pp. 1–14). Rather than replacing physical urbanity, digital elements may amplify, mediate, or selectively reconfigure existing spatial qualities without necessarily altering the material structure itself. The analytical challenge, therefore, lies in distinguishing between structural urban quality and digitally mediated augmentation.

Figure 13 illustrates this conceptual framing, positioning digital interaction as a mediating layer rather than a primary structural driver of urban attractiveness.

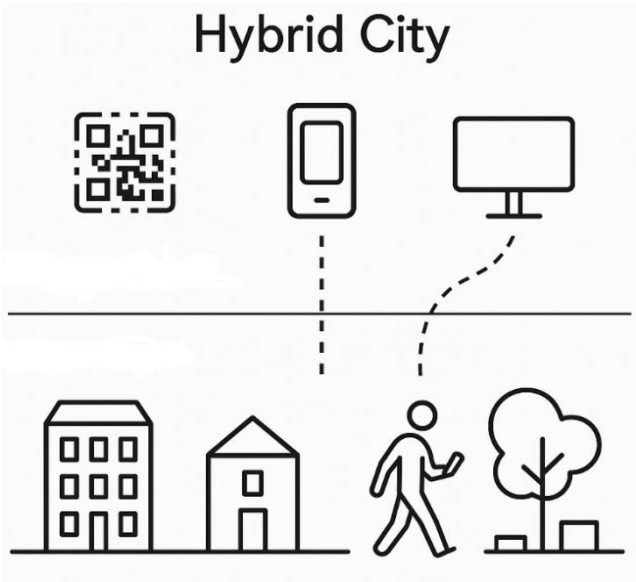


Figure 13. *Hybrid City Model – Structural Positioning of Digital Elements*

The figure conceptualizes urban attractiveness as the result of three interacting dimensions:
(1) spatial quality,
(2) commercial and experiential infrastructure, and
(3) digital interaction.

While urban theory traditionally focuses on the first two dimensions, digital transformation introduces a third layer that may influence perception without necessarily altering the material structure of the city itself (Kitchin, 2014b, pp. 1–14; Yoo et al., 2012, pp. 1398–1408). In practical terms, digital interaction in urban environments often materializes through digital platforms that aggregate and distribute urban information. In this dissertation, the developed City App (Chapter 4.1) can be interpreted as a rudimentary urban information system. It integrates information on places, events, and services and provides them to citizens and visitors through a digital interface. By structuring and distributing urban information across different stakeholder groups, the app operationalizes a basic form of an urban information system within the hybrid city framework.

Despite extensive normative discussions about smart cities and digital urbanism (Hollands, 2008, pp. 303–320; Kitchin, 2014b, pp. 1–14), empirical evidence on how digital transformation shapes perceived urban attractiveness remains limited, particularly in smaller and medium-sized cities (Ahvenniemi et al., 2017, pp. 234–245; Neirotti et al., 2014, pp. 25–36). Most existing research either concentrates on large metropolitan contexts or relies on conceptual frameworks without structural empirical validation (Albino et al., 2015, pp. 3–21). In particular, there is a lack of empirical studies that systematically integrate digital and non-digital factors within a unified analytical framework. As a result, it remains unclear whether digital interaction constitutes a structurally relevant dimension of urban attractiveness or how it relates to established spatial and functional determinants of place perception.

This chapter therefore adopts a deliberately data-driven approach to examine whether digital interaction constitutes a structurally relevant dimension of perceived urban attractiveness. Rather than starting from prescriptive smart city models, it examines how citizens' and visitors' evaluations of urban centers are structurally organized and which dimensions explain perceived attractiveness under conditions of digital transformation.

Using harmonized survey data from multiple medium-sized cities, the analysis proceeds in two steps:

1. Principal Component Analysis (PCA) identifies latent perception structures underlying urban evaluations.
2. Regression models assess the explanatory contribution of spatial quality, retail and service infrastructure, and digital interaction to overall perceived attractiveness.

The objective of this chapter is not to propose a new typology of cities but to empirically examine whether digital transformation constitutes a structurally relevant dimension of perceived urban attractiveness or whether traditional spatial factors continue to dominate perception patterns. In doing so, the analysis addresses the limited empirical evidence on the structural role of digital technologies in shaping urban perception by integrating digital and non-digital dimensions within a unified analytical framework. It thereby complements the individual-level analyses of digitalization presented in other parts of this work by extending the analytical lens to the urban level.

4.2.2 Data and Methods

The empirical analysis draws on standardized city center surveys conducted between 2014 and 2018 in several medium-sized German cities. Table 16 summarizes the data coverage.

Table 16. *Overview of Data Coverage (2014–2018)*

City	Survey Years	Number of Respondents
Lippstadt	2014, 2016, 2018	591 / 422 / 281
Soest	2014, 2018	415 / 238
Meschede	2014, 2018	343 / 109
Bad Sassendorf	2018	89
Sundern	2018	149
Werl	2016	128

The questionnaires included Likert-scale evaluations of inner-city attributes, covering:

- *Urban quality (e.g., cleanliness, safety, atmosphere, public spaces)*
- *Retail and service offerings*
- *Accessibility and transport*
- *Cultural and leisure infrastructure*
- *Digital interaction and online affinity (2018 only)*

To ensure comparability across cities and survey waves, all datasets were standardized and variable coding was harmonized prior to analysis (Harkness et al., 2010; Van de Vijver & Leung, 2021). Given variations in questionnaire design over time, particular attention was paid to aligning item directionality and scaling.

Perceived urban attractiveness was operationalized as a composite index reflecting respondents' overall evaluation of the city center. In the 2014 survey wave, the index was based on six core attributes of inner-city quality. In the 2016 and 2018 waves, the instrument was extended to include additional dimensions such as architectural quality, public spaces, cultural offerings, and accessibility. For each wave, the attractiveness score was computed as the arithmetic mean of the feature ratings included in the respective questionnaire, ensuring conceptual continuity while accommodating the expanded measurement scope in later years. The resulting index represents respondents' overall evaluation of the city center rather than the effect of individual attributes. In the regression analysis, the explanatory variables consist of aggregated perception domains derived

from the PCA, enabling the assessment of how broader perception structures explain variation in overall attractiveness evaluations.

Feature evaluations (F_05_xx) were originally measured on six-point Likert-type scales (1 = very good; 6 = very bad) and recoded accordingly. For the analysis, all evaluative items were recoded so that higher values indicate higher perceived quality. Consequently, higher values of the attractiveness index indicate a more positive overall evaluation of the city center, reflecting favorable perceptions of its spatial, functional, and experiential qualities. Accordingly, perceived urban attractiveness can be interpreted as an aggregated measure of how positively individuals assess the overall quality and appeal of the urban environment.

Digital interaction variables (F_16_xx), available only in 2018, captured smartphone-based information retrieval, app usage, and awareness of digital offerings. Because digital items were not included in earlier waves, they were analyzed separately and not incorporated into cross-wave comparisons.

Due to minor inconsistencies in questionnaire structure across cities and years, some items were excluded from specific comparative analyses in order to maintain structural equivalence of the constructed indices.

The empirical analysis follows a two-stage design. First, Principal Component Analysis is employed to identify latent perception structures underlying urban feature evaluations. Second, regression models are estimated to assess the explanatory contribution of these dimensions to overall perceived attractiveness. The PCA is used in an exploratory capacity, aimed at structural data reduction rather than confirmatory measurement testing (Field, 2024). The objective is to identify coherent perception domains that can subsequently serve as theoretically interpretable predictor constructs.

4.2.3 PCA: Structural Dimensions of Urban Perception

To identify underlying perception structures, a Principal Component Analysis was conducted using the 2018 feature evaluation variables, which provide the most comprehensive and comparable set of urban feature ratings across cities. PCA is a widely used data reduction technique that transforms correlated variables into a smaller number of orthogonal components capturing maximum variance (Abdi & Williams, 2010, pp. 433–459; Jolliffe, 2011, pp. 1094–1096; Field, 2024). In the present study, the method

serves an exploratory purpose: rather than testing a predefined factor model, it aims to summarize the structural organization of urban evaluations.

The PCA analysis focuses on cities for which comparable feature ratings were available within the same survey structure. This includes Lippstadt, Meschede, Sundern, and Bad Sassendorf. Cities with incomplete item sets or differing survey structures were excluded to ensure comparability of the extracted perception components.

Table 17. *Principal Component Analysis Results – Urban Attractiveness*

City	Explained Variance (PC1–PC5)
Lippstadt	45.8%
Meschede	54.3%
Sundern	50.3%
Bad Sassendorf	60.1%

Across the analyzed cities, the first five components explain between 45.8% and 60.1% of total variance. Component interpretation is based on the dominant loading patterns of the underlying feature variables and their conceptual grouping (see Appendix). Following common PCA practice, the number of retained components was determined based on cumulative explained variance and interpretability considerations (Field, 2024). Components beyond the fifth explain only marginal shares of variance and were therefore not interpreted further. While urban theory often distinguishes three broad dimensions of urban quality (e.g., Carmona, 2021), the exploratory PCA reveals a more differentiated perception structure in the empirical data. The PCA results indicate that evaluations of urban attributes exhibit identifiable structural patterns rather than being randomly distributed.

Smaller cities (e.g., Bad Sassendorf, Meschede) show a more concentrated structure, with a larger share of total variance captured by a limited number of components. This pattern may reflect more homogeneous evaluation patterns in spatially compact urban environments. In contrast, Lippstadt exhibits a more differentiated evaluation structure, which may be associated with greater functional diversity and user expectations. Loading patterns vary slightly across cities, but the dominant perception domains remain comparable.

The PCA results indicate that spatial quality and commercial-experiential infrastructure emerge as distinguishable perception domains, which form the basis for the subsequent regression models.

4.2.4 Regression Models: Explaining Urban Attractiveness

Building on the perception domains identified through PCA, three regression models were specified to assess the explanatory contribution of structurally distinct dimensions of urban evaluation. This two-step approach, combining dimensionality reduction with explanatory modeling, is well established in empirical research on perception and evaluation structures (Field, 2024). The models reflect the conceptual separation between material-spatial qualities, commercial-experiential infrastructure, and digitally mediated interaction within the hybrid city framework, and are consistent with prior studies that analyze urban and retail attractiveness through latent perception dimensions and their relative explanatory effects (Reimers & Clulow, 2009, pp. 541–562; Teller et al., 2010, pp. 124–133).

Rather than estimating a single comprehensive model, the analysis deliberately isolates each predictor domain. This modeling strategy serves an analytical purpose: it allows for the assessment of the independent explanatory capacity of each structural dimension without confounding effects. The approach therefore tests whether digital interaction constitutes a structurally comparable layer of attractiveness formation or whether explanatory power remains concentrated in traditional spatial domains.

The dependent variable in all models is the composite urban attractiveness score. Ordinary least squares (OLS) regression was employed separately for each city, resulting in cross-sectional estimations rather than panel models. This decision reflects both the structure of the available data and the objective of comparing perception structures across urban contexts rather than over time.

The regression equation is specified as:

$$Attractiveness_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

where:

- $Attractiveness_i$ is the composite attractiveness score
- X_i represents the respective perception dimension (Spatial Quality, Retail & Offer, or Digital Interaction)
- ε_i denotes the error term

Table 18. *Regression Results – Urban Attractiveness Models*

City	Model	Standardized Coefficients (β)	Explained Variance (R^2)
Lippstadt	Model 1 (Spatial Quality)	0.706***	0.498
	Model 2 (Retail & Offer)	0.630***	0.396
	Model 3 (Digital Usage)	ns	0.000
Meschede	Model 1	0.788***	0.621
	Model 2	0.641***	0.410
Sundern	Model 1	0.802***	0.643
	Model 2	0.799***	0.639
Bad Sassendorf	Model 1	0.790***	0.625
	Model 2	0.797***	0.636
	Model 3	ns	0.000

*Note. *** p < .001; ns = not significant. Models were estimated using ordinary least squares (OLS) separately for each city.*

Across cities, spatial quality demonstrates the strongest explanatory power, accounting for 49.8% to 64.3% of the variance in perceived attractiveness. The standardized coefficients (β = 0.706–0.802) indicate a robust and structurally stable association between perceived spatial qualities, such as cleanliness, safety, and architectural coherence, and overall attractiveness evaluations.

Commercial and recreational infrastructure also shows substantial explanatory relevance. In several cities, particularly Sundern and Bad Sassendorf, retail and service structures approach the explanatory strength of spatial quality, underscoring the continued importance of functional diversity in urban perception.

By contrast, digital interaction does not yield statistically significant effects, with R^2 values close to zero. Digitally mediated behaviors, such as smartphone-based information retrieval or app usage, do not independently shape overall attractiveness evaluations.

Overall, perceived urban attractiveness remains anchored in material and functional characteristics. In medium-sized cities, digital elements operate as supplementary layers rather than primary structural drivers.

4.2.5 Methodological Synthesis

The analyses combine exploratory and explanatory approaches to examine the structural composition of perceived urban attractiveness under conditions of digital transformation.

The PCA revealed that evaluations of urban centers can be reduced to a limited number of coherent perception dimensions. Across cities, a substantial share of variance was captured by a small set of latent components, indicating that urban perception is structured rather than random. These components consistently reflected spatial quality and commercial-experiential infrastructure as dominant perception clusters.

The regression analyses complemented these findings by assessing the explanatory contribution of these dimensions to overall perceived attractiveness. Across all cities, spatial quality exhibited the strongest and most stable association with attractiveness evaluations. Commercial and retail infrastructure also demonstrated substantial explanatory power. In contrast, digital interaction showed no meaningful explanatory contribution in the available data.

These findings suggest that, within the examined medium-sized cities, perceived urban attractiveness remains primarily anchored in material and functional qualities rather than digitally mediated interaction. The digital layer does not structurally redefine urban attractiveness; instead, it appears to operate as a peripheral or supplementary dimension. This finding contrasts with dominant smart city narratives that emphasize the transformative role of digital technologies in shaping urban experience (Hollands, 2008, pp. 303–320; Kitchin, 2014b, pp. 1–14).

Methodologically, the sequential use of PCA and regression allows for a decomposition of perception processes. The PCA identifies latent structure without imposing strong theoretical assumptions, while the regression models assess the relative contribution of dimensions. This combination balances exploratory data reduction with explanatory modeling and provides a transparent analytical pathway from perception structure to attractiveness evaluation.

Digital transformation does not structurally redefine urban attractiveness in the examined cities. Instead, its impact appears supplementary and context-dependent. While digitalization plays a central role at the individual and organizational levels (see previous

chapters), its structural influence on collective urban perception remains comparatively limited. This pattern suggests that the effects of digital transformation are strongly dependent on the level of analysis, supporting multilevel perspectives that emphasize cross-level variation in digitalization processes (Klein et al., 1999, pp. 248–253).

This synthesis reinforces a central theme of the dissertation: digital transformation does not uniformly redefine existing structures. Instead, its effects depend on the level of analysis and the underlying ontological logic of the system under consideration.

4.2.6 Discussion and Limitations

The empirical findings suggest that perceived urban attractiveness continues to be primarily shaped by spatial and functional characteristics of city centers. Across the analyzed cities, factors related to environmental quality, retail offer, and urban atmosphere explain the largest share of variance in attractiveness evaluations. In contrast, digital interaction variables do not emerge as structurally relevant predictors in the regression models. This indicates that digital elements currently function as supplementary layers of the urban experience rather than as primary drivers of perceived urban attractiveness.

From a theoretical perspective, these findings contribute to ongoing debates on the role of digital technologies in urban development. While smart city discourse often emphasizes the transformative potential of digital infrastructures (Hollands, 2008, pp. 303–320; Kitchin, 2014b, pp. 1–14), the results suggest that the fundamental determinants of perceived urban attractiveness remain rooted in physical and functional characteristics of urban space (Gehl, 2011). Digital interaction may enhance information accessibility and user experience, but it does not appear to substitute for core spatial qualities such as safety, cleanliness, and the diversity of urban offerings. In this sense, digital technologies operate more as complementary layers that mediate access to urban environments rather than as structural drivers of urban attractiveness.

A further methodological limitation concerns the measurement level of the survey variables. The urban feature evaluations were collected using Likert-type scales, which are strictly ordinal in nature. In the empirical analysis, these scales are treated as approximately interval-scaled to allow for the application of parametric techniques such as PCA and OLS regression. While this practice is common in empirical social science

research and parametric methods are generally considered robust to such approximations (Eiselen & van Huyssteen, 2023; Norman, 2010, pp. 625–632; Robitzsch, 2020), it implies that the numerical distances between response categories are interpreted as equal, which may introduce a degree of approximation into the estimation results.

In addition, the regression models focus on relative relationships between perception dimensions and the composite attractiveness score. This modeling strategy identifies structurally relevant perception domains but does not capture absolute evaluation levels of individual attributes. Consequently, the analysis explains how different perception dimensions contribute to perceived attractiveness rather than assessing objective quality levels of urban environments.

Finally, regression-based approaches may exhibit sensitivity to individual observations. Given the cross-sectional design and the varying sample sizes across cities and survey waves, the results should therefore be interpreted as structural tendencies in perception patterns rather than deterministic causal relationships.

Another methodological limitation concerns the sampling frame. The survey targeted individuals who were physically present in the respective city centers at the time of data collection. Consequently, the results reflect perceptions of active users rather than potential visitors or non-users. This design implies that the findings capture experienced attractiveness rather than external image perceptions. A further limitation concerns the temporal scope of the dataset. While the most recent survey wave stems from 2018, the analysis focuses on structural perception patterns of urban attractiveness, which tend to evolve gradually rather than change rapidly over short periods of time. A longitudinal comparison of perception structures was not conducted because the survey waves differ in their item composition and measurement scope. This limits generalizability to broader regional populations but strengthens internal validity regarding urban experience. The analysis therefore does not address why individuals choose not to visit a city center, but how those who do visit evaluate its structural qualities. Future research could extend this perspective by incorporating non-visitors or comparative regional samples to differentiate between perceived attractiveness and behavioral access barriers.

4.2.7 Appendix

A: Variable Construction and Harmonization
A1. Urban Feature Variables (F_05_xx)

The survey instruments included a set of items capturing respondents' evaluations of specific inner-city characteristics (block F_05_xx). These variables reflect perceived qualities of the urban environment, including spatial, commercial, and experiential dimensions.

All items were measured on a 1–6 Likert-type scale (1 = very good, 6 = very bad). For analytical purposes, all variables were recoded such that higher values indicate higher perceived quality. This directional harmonization ensures interpretative consistency across models and survey waves.

Examples of included items are:

- F_05_02: Cleanliness
- F_05_03: Safety
- F_05_11: Buildings / architectural appearance
- F_05_15: Overall retail offer
- F_05_xx: Public spaces, cultural offerings, accessibility (depending on wave)

Due to minor variations in questionnaire design across cities and years, some variables were manually recoded, harmonized, or excluded where conceptual equivalence could not be ensured.

A2. Construction of the Urban Attractiveness Score

To enable comparability across cities and survey years, an aggregated urban attractiveness score was constructed at the respondent level.

For each individual i, the composite attractiveness score was calculated as:

$$Attractiveness_i = \frac{1}{k} \sum_{j=1}^{k} Z_{ij}$$

where:

- k denotes the number of harmonized feature items included in the respective survey wave
- Z_{ij} represents the standardized and directionally harmonized evaluation of j

In 2014, the score was derived from six core variables. In 2016 and 2018, the instrument was extended to include additional indicators such as building quality, public squares, cultural offerings, and accessibility.

Prior to aggregation, all items were:

1. Recoded to ensure consistent directional logic
2. Standardized where necessary to account for wave-specific differences

The resulting score captures overall perceived urban attractiveness while accounting for structural differences in survey instruments across time and cities.

B: Principal Component Analysis (PCA) Procedures

Principal Component Analysis (PCA) was conducted using the 2018 survey data to explore the latent structure of urban feature evaluations (F_05_xx block).

The PCA was applied separately for each city to assess whether underlying perceptual dimensions exhibit structural similarity across local contexts. Because PCA was conducted separately for each city, the extracted components are interpreted as structurally comparable perception domains rather than strictly identical latent constructs across cities.

The analysis:

- Extracted the first five principal components
- Used unrotated component extraction
- Focused on variance explanation rather than confirmatory latent modeling

The objective of the PCA was dimensional reduction and structural summarization of perception patterns rather than the estimation of psychometric constructs. Accordingly, formal factor adequacy diagnostics (e.g., KMO, Bartlett's test) were not emphasized, as the analysis serves an exploratory structural function within a broader data-driven framework.

Across cities, the first five components explained between 45.8% and 60.1% of total variance, indicating that perceived urban quality can be meaningfully summarized by a limited number of underlying perceptual dimensions.

C: Regression Model Specification

To assess the relative contribution of different urban perception dimensions to overall attractiveness, separate regression models were estimated for each city.

The general model form is:

$$Attractiveness_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

where:

- $Attractiveness_i$ is the composite attractiveness score
- X_i represents the respective perception dimension (Spatial Quality, Retail & Offer, or Digital Interaction)
- ε_i denotes the error term

Three predictor blocks were operationalized:

- **Spatial Quality**: Aggregated evaluations of safety, cleanliness, architectural appearance, and public spaces
- **Retail & Offer**: Aggregated evaluations of retail diversity, service offerings, and commercial infrastructure
- **Digital Interaction**: Behavioral indicators related to smartphone usage, app interaction, and awareness of digital offerings (available only in 2018)

Each predictor was constructed as the arithmetic mean of harmonized and directionally aligned indicators.

- Estimation method: Ordinary Least Squares (OLS) regression
- Separate models per city
- Models estimated independently for each perception dimension
- Missing values handled via listwise deletion
- No panel modeling was conducted due to differences in indicator availability across waves and cities

The models therefore reflect cross-sectional structural relationships within comparable subsets of the data rather than longitudinal effects.

D: Data Limitations

The empirical dataset combines multiple survey waves across different cities with partially varying questionnaire structures. Not all indicators were available in each year or location. As a result:

- Full panel estimation was not feasible
- Some constructs were operationalized using wave-specific subsets
- Digital interaction variables were available only in 2018

The analyses therefore focus on structurally comparable cross-sectional models. While this limits longitudinal inference, it enables a consistent examination of structural perception patterns across urban contexts.

5. Methodological Reflection on PLS-SEM

Paper 6: **Formative or Reflective? A Decision Framework and Empirical Evidence on Measurement Specification in PLS-SEM**

Authors: Christina Gross, Richard Lackes

Abstract: Measurement model specification is a foundational yet often misunderstood aspect of empirical information systems (IS) research. The distinction between formative and reflective constructs remains a persistent source of methodological ambiguity in Partial Least Squares Structural Equation Modeling (PLS-SEM). This paper revisits the conceptual foundations of measurement specification and develops a structured decision framework to support theory-consistent construct modeling. The framework is operationalized as a process-oriented guide and applied to a Smart Home adoption model. Through systematic respecification and controlled data perturbation, we demonstrate how alternative measurement logics and induced covariance affect construct interpretation and diagnostics. The analyses reveal that structural relationships may remain statistically stable even when the conceptual meaning of constructs changes substantially. Moreover, artificially increased covariance can produce seemingly acceptable reflective diagnostics without resolving ontological misalignment. By combining theoretical synthesis, a formalized decision process, and empirical demonstration, this study shows that statistical adequacy does not guarantee conceptual correctness. The findings underscore the importance of transparent, theory-driven measurement decisions in IS research using PLS-SEM.

Keywords: PLS-SEM, measurement models, formative constructs, reflective constructs, construct validity, structural equation modeling

5.1 Introduction

In empirical research, especially in information systems, the robustness of conclusions often hinges on the quality of the underlying measurement model. Measurement model specification is a central yet frequently misunderstood aspect of empirical IS research. Although the distinction between formative and reflective constructs has been extensively discussed in the methodological literature (e.g., Diamantopoulos & Winklhofer, 2001, pp. 269–277; Jarvis et al., 2003, pp. 199–218; Petter et al., 2007, pp. 623–656), misspecifications remain common in applied PLS-SEM studies. In many cases, measurement decisions are treated as technical modeling choices rather than as theory-driven assumptions about the ontological nature of constructs.

This ambiguity is particularly problematic because measurement specification fundamentally shapes the interpretation of empirical results. As emphasized by Jarvis et al. (2003, pp. 199–218) and Sarstedt et al. (2016, pp. 3998–4010), incorrectly specified constructs can bias parameter estimates, distort effect sizes, and ultimately mislead theoretical conclusions. Importantly, structural relationships may appear statistically stable across alternative specifications, while the conceptual meaning of the underlying constructs changes substantially. Consequently, methodological inconsistencies may remain undetected at the structural level but still alter the theoretical implications of a study.

Against this background, this chapter revisits the theoretical foundations of formative and reflective measurement in PLS-SEM and develops a structured, theory-driven decision process to guide specification choices. Building on established criteria for distinguishing measurement models, the chapter synthesizes prior guidance, clarifies common misconceptions, and empirically demonstrates the consequences of alternative specifications using controlled re-estimations of a Smart Home adoption model. Beyond this focal application, the proposed decision framework provides a methodological lens that informs the specification choices across the empirical studies included in this dissertation, thereby strengthening the overall consistency and validity of the modeling approach.

5.2 Conceptual Foundations and Common Specification Errors

The distinction between formative and reflective measurement models is grounded in fundamental theoretical assumptions about the nature of constructs and their relationship to indicators. Formative constructs are defined as composite representations in which indicators collectively form or cause the construct. In contrast, reflective constructs are conceptualized as latent variables that manifest themselves through correlated and interchangeable indicators (Diamantopoulos & Winklhofer, 2001, pp. 269–277; Jarvis et al., 2003, pp. 199–218).

A central differentiating criterion concerns causal direction. In reflective measurement models, the latent construct is assumed to give rise to its indicators; changes in the construct are expected to produce systematic changes in all indicators. Consequently, reflective indicators should be interchangeable and highly correlated. Removing one indicator should not alter the conceptual meaning of the construct, as each item represents a manifestation of the same underlying phenomenon.

In formative models, the direction of causality is reversed. Indicators define and constitute the construct, often capturing distinct facets of a broader conceptual domain. As a result, formative indicators are not required to correlate, and removing an indicator may fundamentally change the construct's meaning. The construct is therefore sensitive to its specification and depends directly on the theoretical justification of included components (Diamantopoulos et al., 2012, pp. 434–449).

Another important distinction concerns covariance expectations. Reflective indicators are expected to share common variance due to the underlying latent construct. Formative indicators, however, may exhibit low or even negligible correlations because they represent heterogeneous aspects of a conceptual entity. Evaluating formative constructs using criteria designed for reflective models (e.g., internal consistency measures such as Cronbach's alpha or AVE) therefore constitutes a methodological category error (Hair et al., 2017; Petter et al., 2007, pp. 623–656).

Despite extensive methodological guidance, common specification errors persist in empirical IS research. One recurring misconception is the assumption that multi-item constructs are inherently reflective. Researchers often default to reflective modeling

without explicitly assessing causal direction or interchangeability. A second misconception is the belief that statistical model fit or indicator loadings alone determine the appropriate specification. However, measurement model choice is fundamentally a theoretical decision, not a post hoc statistical optimization. Finally, formative constructs are sometimes mischaracterized as reflective constructs with "weak" loadings, ignoring their distinct ontological logic.

These recurring misunderstandings indicate that the distinction between formative and reflective measurement is not merely a technical modeling issue but a conceptual decision embedded in theory development. The following section therefore translates these foundational principles into a structured decision process designed to support theory-consistent measurement specification.

5.3 Decision Framework and Illustrative Application

To support theory-consistent measurement specification, we derive a structured decision process grounded in the conceptual criteria outlined above. Rather than treating measurement choice as an intuitive or post hoc modeling decision, the framework translates core ontological distinctions into explicit evaluative questions. These guiding questions operationalize the theoretical principles distinguishing formative and reflective constructs and make them applicable in empirical research settings.

The decision process is structured around four central criteria:

1. **Causal Direction**: Does the theoretical model assume that indicators collectively form or define the construct (formative), or does the construct represent an underlying latent phenomenon that gives rise to its indicators (reflective)?

2. **Interchangeability**: Are indicators conceptualized as interchangeable manifestations of the same underlying concept (reflective), or does each indicator capture a distinct facet contributing uniquely to the construct's meaning (formative)?

3. **Expected Covariation**: Is shared variance among indicators theoretically expected due to a common underlying construct (reflective), or may indicators vary independently because they represent heterogeneous components (formative)?

4. **Conceptual Sensitivity to Indicator Removal**: Would excluding an indicator leave the construct's conceptual domain intact (reflective), or would it alter the theoretical definition of the construct (formative)?

To illustrate the logic of this process, consider the construct "Carnival." If carnival is defined by the presence of specific elements such as parades, costumes, and music, the first evaluative question, whether indicators cause the construct, already suggests a formative specification. The construct is constituted by its components, and removing one element would alter its conceptual domain. Conversely, if carnival is conceptualized as an underlying festive atmosphere that manifests itself through observable expressions, the causal direction is reversed: the latent construct gives rise to its indicators. In this case, indicators are expected to share variance and may be interchangeable, consistent with a reflective specification.

To ensure transparency and practical applicability, these criteria are operationalized in a BPMN-based decision process (see Figure 14), modeled using ADONIS (BPMN 2.0). The graphical representation formalizes the reasoning and emphasizes that measurement specification constitutes a structured theoretical decision rather than a purely technical modeling step.

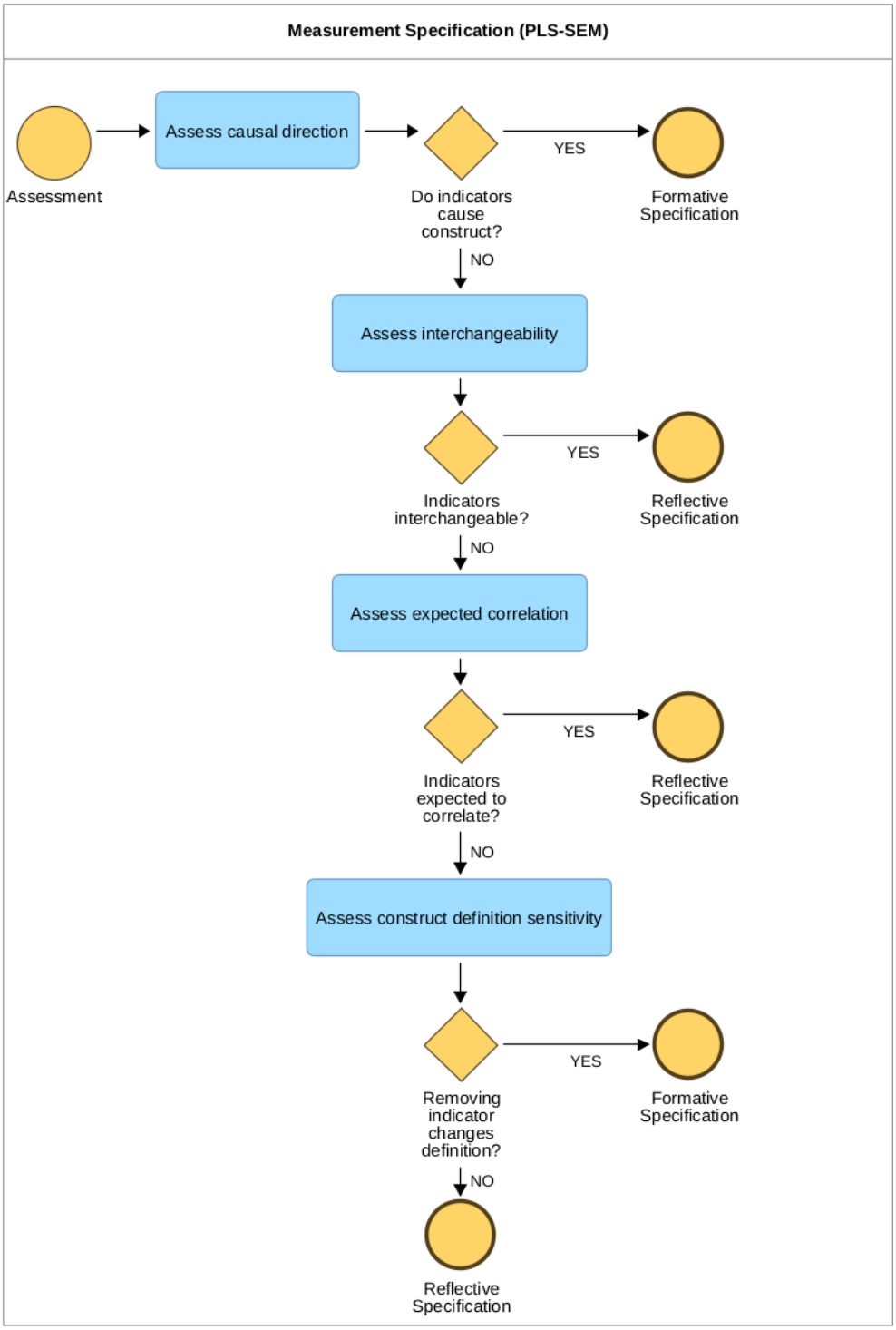


Figure 14. *BPMN-Based Decision Process Measurement Specification*

5.4 Measurement Respecification and Data Structure Effects

While the "Carnival" example illustrates the conceptual distinction between formative and reflective logic in a simplified manner, real-world research settings are typically more

complex. In empirical models, the consequences of measurement decisions are less immediately visible but potentially more consequential.

To move beyond a purely illustrative discussion, the following section applies the measurement framework to one of the empirical studies included in this dissertation. By re-estimating and systematically respecifying selected constructs within the Smart Home adoption model, the practical implications of measurement decisions can be examined under realistic research conditions. In addition to controlled respecifications at the model level, a targeted data perturbation is introduced to simulate indicator redundancy. This third application allows for the analysis of how induced covariance affects reflective validity diagnostics, thereby extending the examination from specification changes to data-structure effects.

5.4.1 Empirical Baseline Model: Smart Home Adoption

To provide a robust empirical basis for the methodological reflection, the Smart Home adoption model (Chapter 3.2) was re-estimated using the final dataset and consistent bootstrapping procedures. Parameter estimation was conducted using the PLS algorithm, while statistical inference was based on bootstrapping, as recommended for variance-based SEM approaches (Hair et al., 2017; Henseler et al., 2009, pp. 332–344). The structural model remained identical to the original specification, including formative and reflective constructs as theoretically justified.

Measurement Model Assessment

The model includes both formative and reflective constructs. Perceived Security and Perceived Comfort are modeled formatively, whereas Perceived Ease of Use and Perceived Costs are specified reflectively.

Formative Constructs

For formative constructs, indicator weights varied substantially, as theoretically expected. In formative measurement models, indicators represent distinct components of the construct and are not required to correlate (Diamantopoulos & Winklhofer, 2001, pp. 269–277; Jarvis et al., 2003, pp. 199–218). Variance inflation factors (VIF) remained below critical thresholds (VIF < 3.3), suggesting no problematic multicollinearity among indicators (Hair et al., 2017).

The heterogeneity of indicator weights confirms that individual indicators contribute distinct facets to the respective constructs rather than representing interchangeable manifestations. In particular, Perceived Security exhibited differentiated indicator contributions, with some indicators showing stronger statistical relevance than others. This pattern aligns with the conceptualization of security as a multidimensional configuration of technical features rather than a uniform latent perception, thereby supporting its formative specification (Diamantopoulos et al., 2012, pp. 434–449).

Reflective Constructs

For reflective constructs, Perceived Ease of Use (PEOU) demonstrated strong indicator loadings exceeding conventional thresholds ($\lambda > 0.70$), indicating satisfactory indicator reliability (Hair et al., 2017). Convergent validity was supported by Average Variance Extracted (AVE) values above 0.50, as recommended in prior literature (Fornell & Larcker, 1981, pp. 46–48). Composite reliability values exceeded recommended cut-offs ($CR > 0.70$), confirming internal consistency (Hair et al., 2017; Henseler et al., 2009, pp. 332–344).

These results support the reflective conceptualization of PEOU as a latent perception manifested through highly correlated and interchangeable indicators, consistent with classical TAM conceptualizations (Davis et al., 1989, pp. 982–1003; Venkatesh et al., 2003, pp. 425–478). Perceived Costs likewise exhibited high loadings and adequate AVE values, indicating reliable measurement and supporting the assumption of indicator interchangeability, a core requirement for reflective specification (Jarvis et al., 2003, pp. 199–218). Discriminant validity was additionally assessed using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT). Both criteria indicated satisfactory inter-construct distinctiveness. However, these diagnostics address discriminant validity between constructs rather than the internal measurement logic or ontological alignment of individual constructs. Thus, while discriminant validity was established, it does not resolve questions concerning formative versus reflective specification.

Structural Model Assessment

The structural relationships remained stable compared to the originally reported results. Path coefficients retained their direction and significance patterns, and the explained variance (R^2) of the endogenous constructs showed only marginal deviations. The

interpretation of R^2 follows established guidelines for PLS-SEM (Hair et al., 2017). Importantly, no hypothesis changed its inferential status as a result of re-estimation. This confirms the robustness of the baseline model and ensures that subsequent measurement respecifications can be interpreted without confounding structural distortions (Sarstedt et al., 2016, pp. 3998–4010).

Table 19 presents the baseline measurement and structural results of the Smart Home model prior to any measurement respecification. The results serve as the reference point for the subsequent comparison.

Table 19. *Baseline Structural Model Results – Smart Home Study*

Construct / Path	Indicator	Loading λ/ Weight w / Coefficient β	AVE	α	ρc	VIF	t-value	p-value	R^2
Panel A: Reflective Measurement Model									
PEOU	PEOU1	$\lambda = 0.955^{***}$	0.742	0.692	0.850	–	13.169	0.000	–
	PEOU2	$\lambda = 0.757^{***}$				–	4.975	0.000	–
PC	PC1	$\lambda = 0.882^{***}$	0.819	0.782	0.901	–	5.427	0.000	–
	PC2	$\lambda = 0.928^{***}$				–	5.387	0.000	–
Panel B: Formative Measurement Model									
PS	PS1	$w = 0.440^{***}$	–	–	–	1.368	3.699	0.000	–
	PS2	$w = 0.245^{*}$	–	–	–	1.384	2.240	0.025	–
	PS3	$w = 0.040^{ns}$	–	–	–	1.559	0.358	0.721	–
	PS4	$w = 0.226^{ns}$	–	–	–	1.791	1.859	0.063	–
	PS5	$w = 0.262^{*}$	–	–	–	1.527	2.331	0.020	–
	PS6	$w = 0.209^{*}$	–	–	–	1.200	2.297	0.022	–
Panel C: Structural Model									
β (PEOU → PU)	–	$\beta = 0.147^{**}$	–	–	–	–	2.878	0.004	–
β (PS → PU)	–	$\beta = 0.361^{***}$	–	–	–	–	6.600	0.000	–
β (PF → PU)	–	$\beta = 0.343^{***}$	–	–	–	–	6.217	0.000	–
β (PU → ATT)	–	$\beta = 0.691^{***}$	–	–	–	–	16.206	0.000	–
β (ATT → BI)	–	$\beta = 0.565^{***}$	–	–	–	–	8.830	0.000	–
β (PU → BI)	–	$\beta = 0.105^{ns}$	–	–	–	–	1.258	0.209	–
β (PC → BI)	–	$\beta = 0.090^{ns}$	–	–	–	–	1.954	0.051	–
β (PEOU → ATT)	–	$\beta = -0.013^{ns}$	–	–	–	–	0.290	0.772	–
Panel D: Explained Variance									
R^2 (PU)	–	–	–	–	–	–	–	–	0.432
R^2 (ATT)	–	–	–	–	–	–	–	–	0.473
R^2 (BI)	–	–	–	–	–	–	–	–	0.433

*Note. * p < .05, ** p < .01, *** p < .001; ns = not significant. Significance based on bootstrapping (5,000 resamples). Parameter estimates are based on the PLS algorithm. Significance levels were obtained via bootstrapping.*

5.4.2 Reflective-to-Formative Respecification: Perceived Ease of Use

To examine the practical implications of measurement model decisions, two constructs were deliberately respecified contrary to their theoretically justified measurement logic. Perceived Ease of Use, originally specified as reflective, was modeled formatively. Conversely, Perceived Security, originally specified as formative, was modeled reflectively. The structural model and estimation settings remain constant; only the measurement logic is altered. Parameter estimates were derived using the PLS algorithm, while statistical significance was assessed via bootstrapping.

Table 20 summarizes the effects of Reflective-to-Formative Respecification.

Table 20. *Effects of Reflective-to-Formative Respecification (PEOU)*

Criterion	Baseline (Reflective)	Respecified (Formative)
Panel A. Measurement Model (Perceived Ease of Use)		
PEOU 1	$\lambda = 0.955^{***}$	$w = 1.058^{***}$
PEOU 2	$\lambda = 0.757^{***}$	$w = -0.119^{ns}$
Panel B. Reliability and Validity		
AVE	0.742	–
Cronbach's α	0.692	–
Composite Reliability (ρc)	0.850	–
VIF (PEOU1, PEOU2)	–	1.388
Panel C. Structural Effects		
β (PEOU → PU)	$\beta = 0.147^{**}$	$\beta = 0.153^{**}$
β (PEOU → ATT)	$\beta = -0.013^{ns}$	$\beta = 0.010^{ns}$
R^2 (PU)	0.432	0.433
R^2 (ATT)	0.473	0.473
R^2 (BI)	0.433	0.433

*Note. λ = reflective loading; w = formative weight; β = structural path coefficient. * p < .05, ** p < .01, *** p < .001; ns = not significant. The structural model remained unchanged. Differences reflect measurement respecification only.*

Measurement Model Effects

Under the formative specification, the indicator weights differed substantially. PEOU1 exhibited a strong and statistically significant weight ($w = 1.058$, $p < 0.001$), whereas PEOU2 showed a negligible and statistically non-significant contribution ($w = -0.119$, $p = 0.755$). Variance inflation factors remained below critical thresholds (VIF = 1.388 for both indicators), indicating no multicollinearity concerns.

However, the distribution of weights reveals a substantial shift in measurement logic. The formative specification concentrates the construct on a single dominant indicator (PEOU1), while the second indicator becomes statistically irrelevant. This outcome is inconsistent with the theoretical logic of reflective measurement, which assumes that indicators are interchangeable manifestations of an underlying latent perception (Jarvis et al., 2003, pp. 199–218).

In the original reflective model, both indicators exhibited substantial loadings (0.955 and 0.757), supporting convergent validity and internal consistency. The formative respecification eliminates the assessment of internal consistency (e.g., AVE, composite reliability) and replaces it with a weighting logic that implies distinct component contributions rather than interchangeable manifestations.

Structural Model Effects

At the structural level, the effects of PEOU remained largely stable. The path from PEOU to Perceived Usefulness slightly increased (from $\beta = 0.147$ to $\beta = 0.153$, $p = 0.005$), while the non-significant relationship with Attitude remained statistically insignificant ($\beta = 0.010$, $p = 0.816$). Explained variance (R^2) values exhibited only minor deviations (PU = 0.433; ATT = 0.473; BI = 0.433).

Thus, although structural relationships appear robust, the underlying measurement logic changes fundamentally. The formative specification alters the ontological interpretation of PEOU: instead of a latent perception reflected by correlated indicators, the construct becomes a weighted aggregation of components. Given the theoretical reflective conceptualization of PEOU in TAM, such a specification would be theoretically inconsistent.

Stability of Explained Variance

A consistent pattern across the analyses is the stability of the explained variance (R^2) despite changes in measurement specification. Although PEOU was alternately specified as formative and reflective, the R^2 values of the endogenous constructs remain nearly unchanged. This result reflects the distinction between measurement and structural models in PLS-SEM. R^2 is determined by the structural relationships between latent constructs, not by the internal composition of their indicators. While respecification alters

the measurement logic and the ontological interpretation of the construct, it does not modify the theoretical structure of the model. As long as the resulting latent variable scores are numerically similar, path coefficients and explained variance remain largely unchanged.

This finding underscores a central argument of this chapter: structural robustness does not imply conceptual correctness. Stable R^2 values therefore cannot be interpreted as evidence of appropriate measurement specification. Instead, construct modeling must be guided by theoretical reasoning rather than by structural performance alone.

5.4.3 Formative-to-Reflective Respecification: Perceived Security

To examine the consequences of an inappropriate reflective specification, Perceived Security (PS), originally modeled formatively, was respecified as a reflective construct while keeping the structural model unchanged. Table 21 summarizes the effects of Formative-to-Reflective Respecification.

Table 21. *Effects of Formative-to-Reflective Respecification (PS)*

Criterion	Baseline (Formative)	Respecified (Reflective)
Panel A. Measurement Model (Perceived Security)		
PS1	$w = 0.440^{***}$	$\lambda = 0.705^{***}$
PS2	$w = 0.245^{*}$	$\lambda = 0.680^{***}$
PS3	$w = 0.040^{ns}$	$\lambda = 0.673^{***}$
PS4	$w = 0.226^{ns}$	$\lambda = 0.776^{***}$
PS5	$w = 0.262^{*}$	$\lambda = 0.719^{***}$
PS6	$w = 0.209^{*}$	$\lambda = 0.545^{***}$
Panel B. Reliability and Validity		
AVE	–	0.471
Cronbach's α	–	0.773
Composite Reliability (ρc)	–	0.841
Panel C. Structural Effects		
β (PS → PU)	$\beta = 0.361^{***}$	$\beta = 0.355^{***}$
R^2 (PU)	0.432	0.432

*Note. λ = reflective loading; w = formative weight; β = structural path coefficient. * p < .05, ** p < .01, *** p < .001; ns = not significant. The structural model remained unchanged. Differences reflect measurement respecification only.*

Measurement Model Effects

Under the reflective specification, all security indicators exhibited statistically significant loadings ranging from 0.545 to 0.776 ($p < 0.001$). Composite reliability ($\rho c = 0.841$) and Cronbach's alpha ($\alpha = 0.773$) exceeded conventional thresholds, indicating acceptable internal consistency. The Average Variance Extracted (AVE = 0.471), however, remained slightly below the recommended benchmark of 0.50. These results suggest that the reflective specification is statistically plausible, yet only moderately supported in terms of convergent validity. Nevertheless, the convergent validity is only moderate, indicating that the indicators do not fully share a strong common latent core.

Conceptually, the reflective respecification implies that the security features (e.g., panic switch, fire detection, simulated presence) represent interchangeable manifestations of an underlying perception of security. This interpretation differs fundamentally from the original formative specification, in which these indicators constitute distinct technical components contributing to a security configuration. Thus, while the reflective model does not exhibit severe statistical deficiencies, it alters the ontological interpretation of the construct. The shift from a configurational to a perceptual understanding of security changes the meaning of the latent variable without substantially affecting statistical fit.

Structural Model Effects

At the structural level, the impact of Perceived Security on Perceived Usefulness remained highly stable ($\beta = 0.355$, $p < 0.001$), closely mirroring the formative baseline specification. The explained variance of endogenous constructs (PU = 0.432; ATT = 0.471; BI = 0.434) exhibited only negligible deviations compared to the baseline model. This stability indicates that the structural relationships are robust to measurement respecification. However, robustness in structural coefficients should not be conflated with conceptual equivalence. The formative and reflective specifications of Perceived Security represent different theoretical assumptions regarding the nature of the construct.

While Sections 5.4.2 and 5.4.3 examined the consequences of changing the measurement logic, the following analysis moves one step further by manipulating the data structure itself. This allows us to disentangle specification effects from covariance effects.

5.4.4 Controlled Data Perturbation: Simulated Indicator Redundancy

Building on the preceding reflective respecification of Perceived Security, a controlled redundancy perturbation was introduced to examine how artificially induced covariance affects reflective measurement diagnostics. The sequential design distinguishes three model configurations reported in Table 22:
(1) the original formative baseline,
(2) the reflective respecification using the unchanged data, and
(3) the reflective specification including a redundant indicator.

Redundancy was introduced only in the third step. Both the formative baseline and the initial reflective respecification were estimated using the original data, thereby isolating the effect of measurement logic from the effect of covariance manipulation.

To simulate conceptual redundancy, an additional indicator (PS1_dup) was constructed as a deterministic linear combination of two existing indicators. This procedure increases shared variance while leaving the conceptual domain of the construct unchanged. The reflective model was then re-estimated including the redundant indicator.

The deterministic construction was deliberately chosen over random noise. Random perturbations would have introduced uncontrolled variance and confounded the interpretation of results. In contrast, the linear combination transparently increases covariance through structural overlap, thereby allowing a direct assessment of how reflective diagnostics respond to redundancy rather than to stochastic fluctuation.

This sequential design enables a clean separation between specification effects and covariance effects:

- The comparison between the formative baseline and the reflective specification isolates the effect of changing measurement logic.
- The comparison between the reflective specification and the reflective model with redundancy isolates the effect of induced covariance.

Had PS1_dup already been included in the formative baseline, both the data structure and the measurement logic would have changed simultaneously. Such a design would not

allow the observed effects to be attributed to a specific source. By introducing redundancy only within the reflective framework, the present approach ensures interpretative clarity.

Table 22. *Effects of Reflective-Respecification and Induced Redundancy (PS)*

Criterion	Baseline (Formative)	Respecified (Reflective)	Reflective + Redundancy
Panel A. Measurement Model (Perceived Security)			
PS1	$w = 0.440^{***}$	$\lambda = 0.705^{***}$	$\lambda = 0.714^{***}$
PS1_dup	–	–	**$\lambda = -0.151^{*}$**
PS2	$w = 0.245^{*}$	$\lambda = 0.680^{***}$	$\lambda = 0.677^{***}$
PS3	$w = 0.040^{ns}$	$\lambda = 0.673^{***}$	$\lambda = 0.663^{***}$
PS4	$w = 0.226^{ns}$	$\lambda = 0.776^{***}$	$\lambda = 0.769^{***}$
PS5	$w = 0.262^{*}$	$\lambda = 0.719^{***}$	$\lambda = 0.715^{***}$
PS6	$w = 0.209^{*}$	$\lambda = 0.545^{***}$	$\lambda = 0.536^{***}$
Panel B. Reliability and Validity			
AVE	–	0.471	0.403
Cronbach's α	–	0.773	0.700
Composite Reliability (ρc)	–	0.841	0.787
Panel C. Structural Effects			
β (PS → PU)	0.361^{***}	0.355^{***}	0.365^{***}
R^2 (PU)	0.432	0.432	0.437

*Note. λ = reflective loading; w = formative weight; β = structural path coefficient. * p < .05, ** p < .01, *** p < .001; ns = not significant. The structural model remained unchanged. Differences reflect measurement respecification only.*

As shown in Panel A, the formative baseline yields heterogeneous indicator weights, consistent with a configurational construct. When respecified reflectively without redundancy, all indicators exhibit substantial and statistically significant loadings. This demonstrates that reflective diagnostics may appear acceptable even when the construct is theoretically formative.

The introduction of PS1_dup produces a structurally revealing pattern. In the reflective model with redundancy, the duplicated indicator loads significantly but negatively ($\lambda = -0.151$, $p = 0.034$). Reflective measurement assumes that covariance arises from a common latent cause. Here, covariance was mechanically induced rather than generated by such a cause. The negative loading indicates that the reflective model compensates for structural redundancy through parameter distortion rather than conceptual coherence.

Panel B further shows that reflective validity diagnostics are sensitive to covariance but not to ontological correctness. While the reflective model without redundancy yields moderate reliability (AVE = 0.471, $\alpha = 0.773$, $\rho c = 0.841$), the addition of the redundant indicator reduces AVE (0.403), Cronbach's alpha ($\alpha = 0.700$), and Composite Reliability ($\rho c = 0.787$). The artificial overlap does not strengthen the reflective representation; instead, it destabilizes it. Although reliability coefficients are commonly interpreted as indicators of internal consistency, they merely capture the degree of shared variance among items. They do not assess whether this covariance originates from a common latent cause or from mechanically induced redundancy. Thus, even established reliability diagnostics remain statistical indicators of covariance rather than safeguards of conceptual validity.

Panel C demonstrates that structural relationships remain largely stable across all specifications. The path coefficient from Perceived Security to Perceived Usefulness changes only marginally ($\beta = 0.361 \rightarrow 0.355 \rightarrow 0.365$), and R^2 for PU remains comparable. Structural stability therefore cannot serve as evidence of measurement correctness.

Despite substantial changes in the underlying measurement logic and covariance structure, the explanatory power of the model remains virtually unaffected. This indicates that structural coefficients may appear robust even when the ontological interpretation of a construct changes or when artificial redundancy is introduced. Consequently, researchers cannot infer the adequacy of measurement specification from stable path coefficients or R^2 values alone. Structural robustness does not imply conceptual validity.

Taken together, the findings illustrate that increased covariance does not guarantee reflective validity when the underlying construct remains conceptually configurational. The redundancy simulation therefore reinforces the central argument of this chapter: covariance-based diagnostics evaluate shared variance, not ontological structure. Even when reflective criteria appear statistically acceptable, conceptual justification remains indispensable for defensible measurement decisions.

5.5 Implications for Research Practice

The analyses demonstrate that measurement specification is not a technical modeling choice but a theory-defining decision. Alternative specifications may leave structural relationships largely stable while simultaneously altering the conceptual meaning of constructs. Consequently, misaligned specifications can distort theoretical claims even when statistical indicators appear acceptable (Sarstedt et al., 2016, pp. 3998–4010).

The empirical respecifications and controlled redundancy simulation further illustrate that covariance-based diagnostics evaluate shared variance rather than construct nature. Statistical adequacy does not guarantee conceptual alignment. Even seemingly acceptable reliability and validity metrics may conceal ontological inconsistencies.

To promote methodological rigor, we recommend:

- Providing an explicit theoretical justification for each measurement specification prior to empirical estimation.
- Transparently reporting the chosen measurement model type and its conceptual justification.
- Applying construct-specific validation criteria (e.g., VIF for formative models; AVE and composite reliability for reflective models).
- Treating measurement specification as a structured decision process. The BPMN-based framework proposed in this chapter offers a formalized and transparent procedure to align construct logic with empirical modeling choices.

Journals and reviewers should encourage authors to make their measurement assumptions explicit and ensure that measurement logic is aligned with theoretical reasoning rather than driven by statistical convenience.

5.6 Conclusion

Formative and reflective measurement decisions must be theoretically grounded and empirically scrutinized. As demonstrated through systematic respecification and controlled data perturbation, alternative measurement logics may leave structural relationships statistically stable while substantially altering the conceptual meaning of constructs. Statistical adequacy alone therefore cannot validate measurement choices.

The findings highlight that covariance-based diagnostics evaluate shared variance rather than construct nature. Even seemingly acceptable reliability and validity indicators may conceal ontological misalignment when measurement logic is inconsistent with theoretical assumptions.

By combining conceptual clarification, a structured decision framework operationalized through BPMN, and empirical demonstration, this chapter provides both methodological guidance and practical tools for theory-consistent construct modeling in PLS-SEM. Ultimately, transparent and theory-driven measurement specification is indispensable for credible theory testing and development in IS research.

6. Multilevel Integration and Implications

6.1 Integrative Insights across Analytical Levels

The six studies included in this dissertation collectively demonstrate that digital technology phenomena cannot be adequately understood when confined to a single analytical level. Although each empirical investigation focuses on a specific context, their combined findings reveal consistent patterns regarding the adoption, evaluation, and contextual embedding of digital technologies across individual, urban, and societal environments.

At the individual level, digital technology use is shaped not only by cognitive evaluations such as perceived usefulness and perceived value but also by psychological and contextual factors including technostress, trust, and situational framing conditions. Across social network usage, smart home adoption, and wearable fitness technologies, adoption intentions emerge as context-sensitive rather than universally stable mechanisms. Cultural environments, lifestyle integration, and crisis contexts influence how digital technologies are interpreted and evaluated. These findings underscore that adoption models remain analytically powerful but require contextual specification.

At the urban level, digital technologies do not operate as autonomous transformation drivers. The analysis of urban attractiveness demonstrates that digital elements function as complementary components within broader structural and spatial configurations. Physical qualities such as safety, accessibility, and coherence of public space remain dominant predictors of perceived attractiveness. Digital integration may enhance experiential aspects of urban environments but does not emerge as a primary structural determinant of perceived attractiveness in the empirical models. This suggests that digitalization in urban contexts is embedded within material and institutional arrangements rather than disruptive in isolation.

Across levels, the studies indicate that digital technologies are embedded within layered socio-technical structures. Individual adoption decisions are influenced by broader contextual conditions, while collective implementation and infrastructural integration shape how technologies are experienced. In crisis situations, such as the COVID-19 pandemic, societal developments directly frame individual perceptions and behavioral

intentions. These cross-level dynamics illustrate that digitalization unfolds through interaction between micro-level evaluations and macro-level framing conditions rather than through linear transformation processes.

Taken together, the findings support a multilevel analytical understanding of digital technology phenomena. Digital technologies are neither purely individual adoption objects nor abstract societal transformation forces; instead, they operate within interdependent socio-technical layers that condition their interpretation, diffusion, and practical impact.

While the dissertation focuses primarily on modeling digital technology adoption, this perspective is complemented by structural urban analysis and methodological reflection. Together, these elements form a coherent analytical architecture that integrates empirical modeling across levels with conceptual and methodological clarification.

6.2 Contextual Embeddedness of Digital Technologies

A central insight emerging from the cumulative findings of this dissertation is that digital technologies unfold within structurally conditioned socio-technical environments. Across empirical domains, digital technology phenomena do not unfold as universally stable or context-independent processes. Instead, their adoption, evaluation, and perceived impact are shaped by cultural, institutional, spatial, and situational conditions.

At the individual level, technology acceptance models demonstrate explanatory power, yet their predictive mechanisms vary across contexts. Cultural environments influence the relative importance of social norms and perceived usefulness; domestic integration shapes the relevance of trust and perceived value; and crisis situations frame how health-related technologies are interpreted. These variations indicate that digital technology adoption cannot be reduced to invariant cognitive mechanisms but must be understood as contingent upon institutional and situational configurations.

In urban environments, digital technologies interact with existing material and structural qualities rather than redefining them independently. The findings indicate that digital elements function as complementary layers within broader urban configurations. While digital integration enhances experiential dimensions, established spatial and functional

characteristics remain structurally dominant. Digitalization in urban contexts therefore operates through augmentation rather than substitution.

The societal dimension further illustrates how framing conditions shape technology-related perceptions. Societal conditions become analytically visible through their measurable influence on individual-level evaluations. Public health crises, regulatory debates, and cultural discourses influence legitimacy and interpretation without necessarily being directly modeled as macro-level variables. Digital technologies are thus embedded in normative and institutional contexts that condition their evaluation and diffusion.

Taken together, these findings support an understanding of digitalization as layered socio-technical embeddedness. Rather than representing uniform transformation trajectories, digital technologies operate within structured environments that mediate their adoption and practical significance. This perspective reinforces the importance of theoretically grounded modeling approaches that account for contextual variation instead of assuming universal behavioral regularities.

6.3 Theoretical Implications for IS Research

The findings of this dissertation offer several theoretical implications for Information Systems research. Rather than proposing a new overarching theory of digitalization, the cumulative results refine and contextualize existing theoretical approaches to digital technology phenomena.

First, the studies reinforce the value of multilevel analytical perspectives in IS research. While technology acceptance models remain powerful explanatory tools at the individual level, their mechanisms are embedded in broader institutional, cultural, and situational contexts. The findings demonstrate that digital technology phenomena cannot be fully understood when analyzed in isolation from their surrounding socio-technical environments. By systematically positioning empirical studies across individual, urban, and societal layers, this work highlights the importance of cross-level sensitivity in theorizing digitalization.

Second, the results emphasize the contextual variability of established adoption constructs. Core constructs such as perceived usefulness, trust, and perceived value do

not operate uniformly across domains. Cultural context, lifestyle integration, and crisis conditions shape their relative importance and interpretation. This suggests that IS research should treat adoption models as adaptable theoretical frameworks rather than universally stable explanatory systems. Contextual specification emerges as a necessary complement to theoretical parsimony.

Third, the integration of digital and non-digital factors in the urban studies extends existing perspectives on digital transformation. The findings indicate that digital elements function as complementary components within broader structural configurations rather than as isolated drivers of change. This perspective challenges implicit techno-deterministic assumptions in parts of the smart city discourse. In this way, it supports a more relational understanding of digital technologies within socio-material environments.

Finally, the methodological reflection on measurement specification contributes to theoretical rigor in IS research. The distinction between formative and reflective constructs is not merely technical but conceptually consequential. By demonstrating how measurement decisions affect construct interpretation without necessarily altering structural results, the dissertation underscores the importance of theory-consistent modeling practices. Theoretical development in IS research therefore depends not only on conceptual innovation but also on transparent and coherent construct specification.

Taken together, these implications support a view of digitalization as a contextually embedded, multilevel phenomenon that requires theoretically grounded and methodologically disciplined modeling approaches. IS research benefits from integrating contextual sensitivity with construct clarity, thereby strengthening both explanatory precision and conceptual coherence.

6.4 Practical Implications

The findings of this dissertation offer practical implications for policymakers, urban planners, organizations, and technology providers. While the studies are grounded in academic modeling approaches, their results provide context-sensitive insights for real-world digital initiatives.

For policymakers and urban decision-makers, the results suggest that digital tools should be integrated as complementary components rather than assumed as standalone

transformation drivers. The analysis of urban attractiveness demonstrates that physical infrastructure, safety, accessibility, and spatial coherence remain dominant predictors of perceived quality. Digital applications such as city apps can enhance engagement and experiential value, but they cannot substitute for structural urban qualities. Consequently, digital strategies in urban development should be aligned with broader spatial and institutional planning rather than pursued in isolation.

For organizations and technology providers, the findings emphasize the importance of contextual sensitivity in technology adoption strategies. Adoption intentions are influenced not only by functional utility but also by trust, perceived value, and integration into everyday routines. In domestic and health-related contexts, perceived security and lifestyle compatibility play critical roles. Technology providers should therefore move beyond purely feature-driven communication and address user concerns related to control, data security, and tangible benefits.

In crisis contexts, such as public health emergencies, digital technologies are interpreted within broader societal framing conditions. The wearable fitness tracker study indicates that perceived value remains a central driver of usage intention even in heightened awareness situations. This suggests that crisis communication alone does not guarantee adoption; perceived personal relevance and benefit remain decisive. Policymakers and health authorities should therefore combine informational campaigns with clear demonstrations of practical value.

For researchers and practitioners involved in empirical evaluation, the methodological findings underscore the importance of transparent construct specification. Measurement decisions influence interpretation and practical recommendations. Careful alignment between theoretical definitions and statistical modeling enhances the reliability of derived implications and prevents misleading conclusions based solely on acceptable fit indices.

Overall, the practical implications of this work highlight that digital technologies operate within layered socio-technical contexts. Effective digital strategies require alignment between technological functionality, user perception, institutional frameworks, and structural environments. Digitalization should therefore be approached as an embedded process that demands contextual calibration rather than universal implementation templates.

6.5 Limitations and Future Research

Despite the integrative scope of this dissertation, several limitations should be acknowledged. First, the empirical studies are based on cross-sectional survey designs. While suitable for modeling relationships between latent constructs, such designs do not allow for longitudinal analysis of changing perceptions or adoption dynamics over time. Future research may extend these findings through longitudinal or panel-based approaches to examine how digital technology evaluation evolves.

Second, although the dissertation adopts a multilevel analytical perspective, macro-level institutional variables are not directly operationalized within the empirical models. Societal and contextual influences are incorporated primarily as framing conditions rather than as explicitly modeled higher-level constructs. Future studies could apply hierarchical or level-spanning modeling techniques to further explore cross-level interactions in more complex institutional environments.

Third, the empirical contexts focus predominantly on European and selected international samples. While cross-cultural elements are considered in individual studies, broader geographic diversity may enhance the generalizability of findings. Comparative studies across different regulatory or socio-economic systems could further refine understanding of contextual variability.

Finally, the methodological contribution emphasizes measurement specification within PLS-SEM-based research. Although the proposed framework enhances transparency and conceptual alignment, ongoing methodological debate in IS research suggests that alternative modeling approaches may provide complementary perspectives. Future research may therefore explore how different analytical techniques influence construct interpretation and theoretical conclusions.

These limitations indicate opportunities for further refinement and extension of cross-level digitalization research. Continued integration of contextual awareness with methodological rigor remains a promising avenue for advancing IS research on digitalization.

7. Conclusion and Outlook

7.1 Summary

This dissertation examined digitalization as a multifaceted socio-technical phenomenon unfolding across economy and society. While digital technologies are frequently framed as large-scale transformation drivers, research often remains confined to isolated analytical levels. Addressing this fragmentation, the dissertation adopted a multilevel perspective to investigate how digital technologies are adopted, evaluated, and embedded across diverse empirical contexts.

Across analytical levels, the findings demonstrate that digital technology phenomena are shaped by contextual and structural conditions rather than universal adoption mechanisms. Adoption intentions are influenced by cultural environments, trust considerations, lifestyle integration, and situational framing conditions. In urban contexts, digital elements operate as complementary components within broader structural configurations, enhancing experiential dimensions without replacing material infrastructures. Digitalization therefore emerges as a context-sensitive and embedded process rather than a linear transformation trajectory.

Complementing the empirical investigations, the dissertation contributes a methodological reflection on measurement specification in Partial Least Squares Structural Equation Modeling (PLS-SEM). By illustrating the conceptual consequences of formative and reflective construct decisions, the research emphasizes that construct specification is integral to theoretical clarity and interpretability.

Taken together, the dissertation advances a modeling-oriented and context-sensitive understanding of digital technology phenomena. By integrating multilevel empirical analysis with methodological rigor, it contributes to a structured perspective on digitalization that balances contextual awareness with analytical precision.

The findings further demonstrate that digitalization cannot be adequately theorized as a single-level phenomenon, as this would neglect the interaction between individual evaluation mechanisms, contextual conditions, and structural environments that jointly shape technology adoption and impact.

7.2 Overall Contribution

The overall contribution of this dissertation lies in integrating multilevel empirical analysis with methodological rigor in the study of digital technology phenomena. Instead of advancing a single unifying theory, it contributes through structured empirical integration and methodological clarification.

Empirically, the dissertation provides evidence across diverse domains, including social network usage, smart home adoption, urban digital infrastructures, and wearable health technologies. By systematically positioning these studies within a multilevel analytical framework, the research demonstrates that digital technology phenomena manifest differently depending on contextual and structural conditions. This cross-domain integration contributes to a more differentiated understanding of digitalization in economy and society.

Conceptually, the dissertation reinforces the view of digitalization as a layered socio-technical process. The findings challenge implicitly deterministic assumptions that treat digital technologies as isolated transformation drivers. Instead, digital elements operate within institutional, spatial, and cultural environments that mediate their adoption and perceived impact. By emphasizing contextual embeddedness, the research contributes to a more relational and less reductionist understanding of digital technologies in IS scholarship.

Methodologically, the dissertation strengthens theoretical clarity through structured guidance on measurement specification in PLS-SEM. By highlighting the conceptual implications of formative and reflective construct decisions, the research underscores that methodological rigor is integral to theoretical advancement. Transparent construct modeling enhances interpretability and supports cumulative knowledge development in IS research. The dissertation demonstrates that methodological rigor and contextual sensitivity constitute complementary dimensions of cumulative IS research rather than competing priorities.

Building on this, it contributes a coherent analytical perspective that combines contextual sensitivity, multilevel positioning, and methodological discipline. Its primary value lies not in theoretical abstraction, but in structured empirical modeling that enhances clarity, comparability, and conceptual precision in the study of digitalization.

In this regard, the dissertation further shows that digital technology phenomena require cross-level theorizing rather than isolated analytical explanations.

7.3 Outlook

The increasing complexity of digital environments calls for theoretically grounded and methodologically transparent research approaches. As digital infrastructures become more embedded in everyday life, questions of contextual variation, cross-level interaction, and socio-technical embeddedness will gain further importance.

Future research on digitalization may benefit from extending multilevel analytical perspectives through longitudinal designs and explicit cross-level modeling techniques. Examining how digital technology perceptions change over time and how institutional conditions shape adoption trajectories could deepen understanding of dynamic digital environments. Greater integration of material, spatial, and digital dimensions may further refine insights into hybrid socio-technical systems.

From a methodological standpoint, continued attention to construct specification and transparent modeling practices remains essential. As empirical IS research increasingly addresses complex and context-sensitive phenomena, clarity in theoretical definitions and measurement logic becomes a prerequisite for cumulative knowledge development.

Overall, digitalization research will continue to face the challenge of balancing analytical precision with contextual awareness. By combining structured empirical modeling with sensitivity to socio-technical environments, future research can contribute to a more differentiated and robust understanding of digital technology phenomena in economy and society.

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