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Maximilian SCHWING

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Directeur de thèse :

Mr. Lars MEYER-WAARDEN, Professor, Université Toulouse 1 Capitole

Mr. Marc KUHN, Professor, Baden-Wuerttemberg Cooperative State University Stuttgart

JURY

Rapporteurs Mrs. Silja HOFFMANN, Professor, University of the Bundeswehr Munich
Mrs. Jessie PALLUD, Professor, EM Strasbourg Business School

Suffragants Mrs. Sandra LAPORTE, Professor, Université Toulouse 1 Capitole

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Introduction

"I think our obsession with ownership is at a tipping point

and the sharing economy is part of the antidote for that."

Richard Branson, 2016

A core task of marketing is to facilitate exchange between buyers and sellers, which traditionally has involved the permanent transfer of ownership (Bagozzi, 1974). In the recent past, developments in information and communications technology, growing consumer awareness, and anti-materialism consumer behavior have shaped new forms of exchange that challenge the classical way marketing operates to facilitate exchange. The term "sharing economy" represents a new and sharing-based consumption mode, allowing people to consume without having to buy or own. It has disrupted many well-established industries, such as the accommodation and transportation sector, by offering easy-to-access and flexible consumption options without the responsibility of ownership (Eckhardt & Bardhi, 2015; Kumar et al., 2018). In 2015, the global market size of the entire sharing economy was estimated to be $15 billion, and it was expected to grow to $335 billion by 2025 (PwC, 2015, 2018). Although the COVID-19 pandemic has radically affected the sharing economy since the beginning of the year 2020 (Hossain, 2021) because sharing services are often related to personal exchange activities, the global market size was valued at $113 billion in 2021 and is expected to reach $600 billion by 2027 (Digital Journal, 2022).

Simultaneously, in the last decade, sharing-based consumption modes have attracted research attention, both within and outside the marketing domain. From an academic perspective, the term sharing economy can be understood as an umbrella concept that encompasses a variety of non-ownership sharing-based consumption modes (Acquier et al., 2017; Akbar, 2019; Minami et al., 2021), e.g., access-based consumption (Bardhi & Eckhardt, 2012), product service systems (Akbar & Hoffmann, 2020), commercial sharing systems (Lamberton & Rose, 2012), lateral exchange markets (Perren & Kozinets, 2018), prosumption (Ritzer & Jurgenson, 2010), collaborative consumption (Botsman & Rogers, 2010), the collaborative economy (Dredge & Gyimóthy, 2015), the gig economy (Gleim et al., 2019), the platform economy (Dann et al., 2020) and peer-to-peer sharing economy (Wirtz et al., 2019).

Concerning a clear definitional understanding for our study, we draw on the definition of the "sharing economy continua" developed by Eckhardt et al. (2019) as it is the most recent framework to differentiate between sharing economy entities from a marketing and consumer behavior perspective. Based on a set of seven criteria, the sharing economy is defined as "a scalable socioeconomic system that employs technology-enabled platforms to provide users with temporary access to tangible and intangible resources that may be crowdsourced" (Eckhardt et al., 2019, p. 7). The first criterion refers to the fact that temporary access rather than permanent ownership is exchanged between the involved actors. For example, car sharing services (e.g., Zipcar) offer benefits to their users by using a car for a fixed period of time without ownership responsibilities (Bardhi & Eckhardt, 2012). The second criterion defines that sharing economy concepts involve economic transactions that transfer value from one entity to another. Therefore, sharing activities without economic transactions, e.g., car sharing between friends, are not considered (Belk, 2014). The third criterion refers to platform reliance, as sharing transactions are usually mediated by internet-based platform applications (Perren & Kozinets, 2018). Therefore, a classical car rental station is not considered to be part of the sharing economy, as it is a direct engagement with the rental station without platform interaction. The fourth criterion refers to the enhanced role that customers can perform. For example, consumers can participate in both the demand side and the supply side of sharing transactions (Ritzer & Jurgenson, 2010), and some sharing economy examples require users to maintain the shared good (Eckhardt et al., 2019). The fifth criterion refers to the fact that supply can be crowdsourced from more than one individual consumer. For instance, in on-demand ride services (e.g., Uber) drivers pool their time and resources to provide a comprehensive service.

From a practical market perspective, many sharing-based business models have emerged and gained acceptance where the focus is on providing temporary access to goods rather than selling them (Belk, 2014). Two of the best-known and most cited examples (Sutherland & Jarrahi, 2018), which have heavily disrupted their respective industry, are Airbnb (accommodation sharing; Zervas et al., 2017) and Uber (on-demand ride sharing; Min et al., 2019). Former research and existing literature highlight the several advantages of the sharing economy, e.g., how it creates business opportunities (Murillo et al., 2017; Wilhelms et al., 2017), enables higher utilization of goods (Frenken, 2017; Gerwe & Silva, 2020; Jiang & Tian, 2018), generates collaboration in communities (Bouncken & Reuschl, 2018; Frenken & Schor, 2017), and is more environmentally sustainable (Böcker & Meelen, 2017; Geissinger et al., 2019). The three most influenced industries are the accommodation sector, the sector for retail and consumer goods, and the transportation sector (BCG, 2017; PwC, 2015, 2018). The market for sharing-based consumption in the transport sector is also referred to as shared mobility, which encompasses a range of transportation models and well-known practical examples (e.g., Uber, Zipcar, and Lime) that will be discussed in more detail in the next section.

1 The Context of Shared Mobility

"In the future,

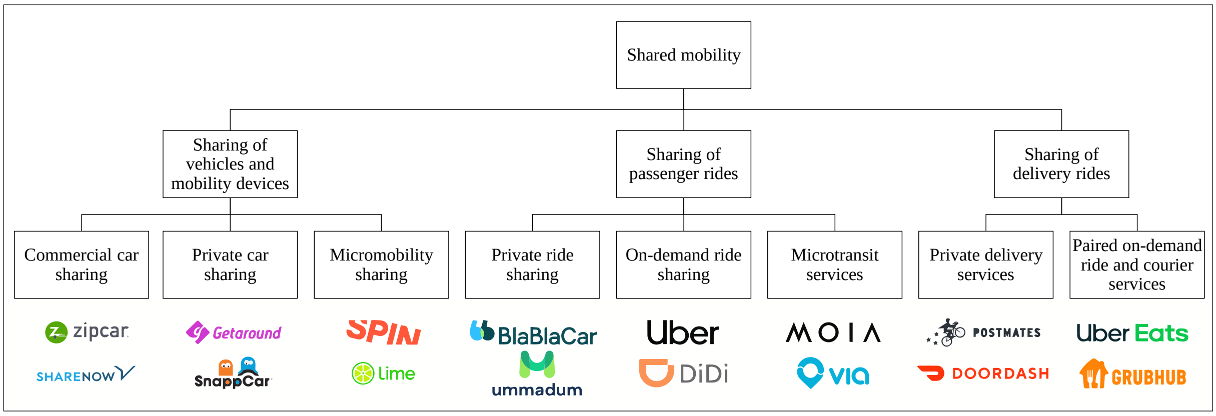
you will be able to move anywhere, at any time and by any mode of transport

without needing to own a vehicle."

Sampo Hietanen, 2017

The topic of shared mobility sits within the broader phenomenon known as the sharing economy and has attracted interest in the academic literature recently. Similar to the term sharing economy, it is vital to have a commonly accepted terminology for shared mobility and what transportation concepts it encompasses (Castellanos et al., 2022), as this term is often used not only in the academic literature but also by policymakers and practitioners. For our research, we adopt the definition suggested by Shaheen and Chan (2016) and designated as norm definition by the Society of Automotive Engineers (SAE International, 2021), as, similar to Eckhardt et al. (2019) for the sharing economy, the term shared mobility is described as an umbrella concept that includes different sub-concepts that can differ along defined criteria. Accordingly, the term shared mobility is defined as "the shared use of a vehicle, bicycle, or other mode that enables users to have short-term access to transportation modes on an as-needed basis" (SAE International, 2021; Shaheen et al., 2020; Shaheen & Chan, 2016). Hence, the concept of shared mobility includes different short-term and as-needed transportation forms that can differentiate in several aspects. The unifying element is that they all include a mobility asset as a central element that is collaboratively consumed to satisfy either a direct mobility need or a mobility-related need. Depending on the specific needs and related mobility asset, shared mobility can be further categorized into three clusters (see Figure 1).

Figure 1: Categorization of Shared Mobility (adapted from Shaheen et al., 2020)



First, the sharing of vehicles or mobility devices, whereby commercial car sharing (e.g., Zipcar), private car sharing (e.g., Getaround), and micromobility sharing (e.g., Spin) can be grouped. In commercial car sharing, the vehicle is provided by the sharing platform itself (marketer-provided sharing; Bardhi & Eckhardt, 2012), whereas in private car sharing, the shared vehicle is provided by private individuals, and the exchange is mediated by the sharing platform (peer-provided sharing; Wirtz et al., 2019). Shared micromobility services are typically marketer-provided services that include a range of light-weight, human-powered, or electric vehicles (e.g., e-scooters, bikes, e-bikes) that operate at speeds typically not exceeding 25 kph (Abduljabbar et al., 2021). The second cluster is the sharing of passenger rides, where private ride sharing (e.g., BlaBlaCar), on-demand ride sharing (e.g., Uber), and microtransit (e.g., MOIA) can be summarized. Private ride sharing (also called carpooling) is the sharing of rides with similar origin-destination pairings, where a driver travels for his own transportation needs and offers empty seats to passengers (Hartl et al., 2020). On-demand ride sharing (also called ride sourcing) is a for-profit-based concept that connects drivers with passengers to provide professional transportation services (Min et al., 2019). Microtransit is a technology-enabled transit service that typically uses multi-passenger shuttles to provide service on demand or on a fixed schedule with dynamic or fixed routing (Shaheen et al., 2020). The third cluster is the sharing of delivery rides, which can be differentiated into private delivery services (e.g., Postmates) and paired on-demand ride and courier services (e.g., UberEATS).

2 Research Motivation

In shared mobility markets, multiple agents, including public and private providers, seek to develop new and innovative products and services that often aim to address deficiencies in public infrastructure (e.g., highways, streets, parking) and public transportation (e.g., last-mile connectivity), which has historically been the exclusive purview of public authorities (Cohen & Kietzmann, 2014). Consequently, shared mobility has gained adoption in cities around the world as an innovative means of improving urban mobility (Shaheen et al., 2020; Shaheen & Chan, 2016). In addition, shared mobility can provide consumers with greater flexibility and convenience, including areas with less comprehensive and readily available mobility options and limited public transportation alternatives (Ballús-Armet et al., 2014) or where owning a personal vehicle may be impractical or too expensive (Münzel et al., 2019). Furthermore, shared mobility can have environmental benefits through optimized usage of underutilized mobility assets (Wilhelms et al., 2017), while reducing the number of individual vehicles on the road. Consequently, shared mobility is expected to reduce traffic congestion and improve air pollution in urban areas, especially during peak travel times (Standing et al., 2019). Overall, shared mobility is a promising application of the sharing economy in the transportation sector that has the potential to transform the way that people move around in cities and other areas, e.g., by offering more flexibility and reducing the environmental impact of transportation.

2.1 Bright Sides of Shared Mobility for Sustainable Consumption

In September 2015, the United Nations published the 17 Sustainable Development Goals (SDGs) as part of the 2030 agenda for sustainable development (United Nations, 2022). Sustainable transport is one of the main issues in the sustainable development agenda that positively conditions several SDGs and serves as a prerequisite for progress in achieving goals related to, e.g., healthy living, air quality, and the reduction of air pollution (United Nations, 2016). According to recent studies and the prevailing literature, the enhanced use of shared mobility can contribute to the SDGs (Chaudhuri et al., 2022; Lukasiewicz et al., 2022), including good health and well-being (SDG3), sustainable cities and communities (SDG 11), and responsible consumption (SDG 12). For instance, the enhanced use of shared mobility options can contribute to good health and well-being because it mitigates the impacts of climate change by promoting the use of better-utilized, more sustainable vehicles and, hereby, helping reduce greenhouse gas emissions (Amatuni et al., 2020; Martin & Shaheen, 2011). Moreover, access-based, on-demand shared mobility solutions reduce the need for vehicle ownership (Albinsson et al., 2019; Fritze et al., 2020) by providing temporary access to affordable and convenient transportation (Almannaa et al., 2021; Kopplin et al., 2021), and by promoting more active transportation such as the use of shared micromobility modes (Abduljabbar et al., 2021; Biehl et al., 2019). In terms of sustainable cities and communities, it supports the development of urban space by helping to reduce the number of cars on the road (Hardt & Bogenberger, 2019; Smith & Schwieterman, 2018), and by promoting the enhanced use of existing public transportation combined with shared mobility solutions for first and last mile connectivity (Gössling, 2020; McKenzie, 2020). Moreover, reducing reliance on modes of motorized individual transportation (e.g., cars) is likely to promote the development of more sustainable transportation infrastructure, such as bike lanes and charging stations for shared electric vehicles (Hosseinzadeh et al., 2021; Wang & Chen, 2020). Finally, the use of shared mobility services contributes to responsible consumption by reducing the demand for individual ownership (Cohen & Kietzmann, 2014) and encouraging the sharing of resources in terms of mobility assets (Hartl et al., 2020).

2.2 Dark Sides of Shared Mobility and Negative Side Effects

While the use of shared mobility is seen by many people as a sustainable and forward-thinking mode of transportation, counterviews point to potential risks and problems. Some counterviews can be traced back to the causes of consumer behavior (Gössling, 2020). For example, shared mobility services provide temporary access to transportation alternatives that may not have been accessible before. Based on the hypothesis that through car sharing it becomes easier for young people to access cars and that young drivers are more likely to be in a car crash than adult drivers, an analysis of car crashes from 224 counties showed that the entry of car sharing significantly increases car crashes of teenage drivers (Choi & Lee, 2019). While car crashes may depend on the experience level of the drivers, other consumer behavior-related downsides are attributed to misbehavior. Consumer misbehavior is the deliberate ignoring of commonly accepted rules of conduct in a consumption situation by improper handling, damaging, or overusing the product (Fullerton & Punj, 2004). Consumer misbehavior in sharing-based consumption is a significant challenge and has therefore been studied in the context of shared mobility (e.g., e-scooter sharing; Useche et al., 2022, bike sharing; Jin et al., 2022; Srivastava et al., 2022, car sharing; Schaefers et al., 2016). In particular, the use of shared micromobility (e.g., e-scooter sharing and bike sharing) is the focus of intense discussions about consumer misbehavior, as vandalized vehicles, randomly parked vehicles, and prohibited riding with a pillion, represent massive problems for cities (Gössling, 2020). These issues even led cities to ban e-scooter sharing services. Paris was labeled as a pioneer when it introduced e-scooter sharing in 2018, as the city's authorities sought to promote non-polluting forms of urban transportation. But as e-scooters have become more popular, especially among young adults, they have also become more dangerous: in 2022, e-scooter crashes in Paris resulted in three deaths and 459 injuries (The Guardian, 2023). So, in early April 2023, Paris citizens were asked in a referendum to vote "for or against" e-scooter sharing, and a large majority of 89% voted in favor of banning the devices from the streets of the French capital (Reuters Media, 2023). This decision has been followed worldwide and many other cities are weighing the future of e-scooter sharing on their streets. Similarly, Copenhagen and Montreal both already banned e-scooter sharing in 2020, although Copenhagen agreed to return them the following year under strict conditions (Nouvian, 2023). For example, trips can no longer start or end in a dense city area and can only be parked in designated zones. In addition, the provider will need to work with the City to ensure that the service is affordable, safe, and sustainable (The Local Denmark, 2021).

Other opposing views are related to the nature of the sharing-based service. Shared mobility services, or any sharing economy service, are per definition platform-based online services that require the provision and disclosure of personal information, such as name, date of birth, and place of residence, for registration. The use of online services has long been associated with privacy threats because providing personal data makes users vulnerable to accidental or intentional harm (Dinev & Hart, 2006; Malhotra et al., 2004). Moreover, shared mobility services are usually location-based services (Wang & Lin, 2016). A location-based service detects where the device is located and allows users to share their past or current location information online (Tsai et al., 2009). Hence, such apps can also track a user's location and provide information such as routes, attractions, and traffic conditions (Li et al., 2019). Consequently, high levels of user anxiety regarding privacy are considered an additional barrier to the adoption and use of sharing-based consumption (Lutz et al., 2018; Teubner & Flath, 2019).

Finally, there are opposing views related to vehicles for shared mobility itself. Some research discusses that, instead of replacing the use of motorized individual vehicles (e.g., private cars), using shared mobility, and particular e-scooters, generates additional trips that would not have been made before (e.g., with recreational purposes, Chang et al., 2019) or replaces trips that would have been walked before (Christoforou et al., 2021; Laa & Leth, 2020). Other research raises concerns about the sustainability of the transportation devices themselves because the lifespan of, for example, e-scooters heavily impacts the environmental benefits (Hollingsworth et al., 2019; Moreau et al., 2020). In this regard, Hollingsworth et al. (2019) suggest that assuming a two-year lifespan, the lifecycle greenhouse gas emissions associated with e-scooter use are 65% higher than those of displaced modes. Similarly, Moreau et al. (2020) conclude that, at the time of the assessment, the shared use of e-scooters had a greater greenhouse gas emissions impact than the modes of transportation they could replace. Based on their assumptions and results, they emphasize that extending the lifespan of shared e-scooters to at least 9.5 months will make them an environmentally friendly choice for mobility (Moreau et al., 2020). However, the discussion concerning the sustainability of e-scooters is divided, as other publications are stating that e-scooters can be an alternative to private vehicles for short trips (Hardt & Bogenberger, 2019; Smith & Schwieterman, 2018) as well as being more energy efficient than other modes of transport (Ishaq et al., 2022).

2.3 Innovations in the Shared Mobility Sector

As outlined in the previous sections, shared mobility and especially shared micromobility is a relevant but also controversial topic regarding future transportation and mobility needs. Therefore, shared mobility solution providers are continuously innovating their products and services to further enhance the benefits and to overcome the negative side effects of existing solutions (Jin et al., 2022; Schaefers et al., 2016; Useche et al., 2022). In this regard, at least three main directions of innovations can be described.

The first direction of innovative services in the shared mobility markets refers to mobility-as-a-service (MaaS), a recent integrating concept that is gaining momentum in both the scientific world and the market (Hasselwander et al., 2022; Pangbourne et al., 2020). The idea behind MaaS is to provide users with a single, integrative platform ("one-stop-shop") for all kinds of transportation needs, allowing them to plan and book transportation in real-time, based on their preferences and budget, and simultaneously enhancing a shift to a more multi-modal mobility behavior (Matyas & Kamargianni, 2021; Wong et al., 2020). Moreover, MaaS platforms incorporate data analytics and machine learning algorithms to provide personalized recommendations, based on travel history (Reyes García et al., 2020). Platform companies, such as Whim, Citymapper, and MaaS Global, are leading the way, partnering with various transportation providers and integrating public transit to offer users a seamless experience.

The second direction aims to make even more efficient use of the car resources that already exist (Nansubuga & Kowalkowski, 2021; Turoń, 2022), to overcome problems related to resource efficiencies. Since cities with low population densities and rural areas are likely to remain car-dependent for the foreseeable future, car-based mobility services such as car and ride sharing can make a valuable contribution (Illgen & Höck, 2020; Mounce & Nelson, 2019). A typical private car is parked most of the time, and many of these cars prevent road space from being used for other purposes, such as bicycle lanes (Brown et al., 2020). Car-based shared mobility services can thus both directly enable more resource-efficient mobility and indirectly contribute to sustainable urban development (e.g., repurposing of vacated parking spaces).

The third direction is to make the most of the existing potential of shared micromobility. While public transportation is considered to be a highly efficient and environmentally friendly mode of transportation, it fails to take people everywhere they want to go. Shared micromobility services are an important part of the multi-modal mobility mix as they take care of the first-and-last-mile problem, especially in cities where the density of public transport stations is low (Abduljabbar et al., 2021). However, shared micromobility services are so closely linked to consumer misbehavior, as discussed in the previous section, that some cities have already banned the services in their current setup. Micromobility service providers, therefore, need to innovate and evolve their business models to solve these problems to compete in the marketplace. Research on consumer misbehavior in shared mobility markets suggests that sharing service providers can counteract misbehavior by building more personal relationships with customers, reducing interpersonal anonymity, and, most importantly, increasing customers' identification with the community (Jin et al., 2022; Schaefers et al., 2016; Srivastava et al., 2022).

2.4 Closed-campus Micromobility

One focus field of innovation in the shared micromobility segment that aims to overcome limitations of existing public available solutions and that is attracting more and more attention inside and outside academia is the so-called closed-campus micromobility (Buehler et al., 2021; Eccarius et al., 2021; Sun & Duan, 2021; Sunio et al., 2020). Shaheen and Chan (2016) first mentioned the term "closed-campus" referring to bike sharing systems that "are increasingly being deployed at university and office campuses and are only available to the particular campus community they serve" (Shaheen & Chan, 2016, p. 580). For our further research, we use the term "closed-campus micromobility" that describes a transportation solution that provides access to shared use of micromobility vehicles (e.g., bikes, e-scooters) only available for members of a certain organization. Regardless of whether the service is freely accessible or only available in a closed environment, the operating model of a shared micromobility service can be station-based, dockless, or a hybrid of the two models (Shaheen et al., 2020). In a station-based system, users access and return the micromobility device at fixed stations. In a dockless, or free-floating, system, users can access and return the micromobility device at any location within a predefined geographic region. A hybrid system is a combination of the two operating models. Past research on station-based micromobility systems suggests that stations in areas with more employment or nearby attractions are more efficient because more people are arriving and departing (Faghih-Imani et al., 2017). This is consistent with the analysis of e-scooter usage data, which indicates that e-scooters are most frequently and carefully used by defined groups of users near universities and in central business districts (Bai & Jiao, 2020; Caspi et al., 2020; Reck et al., 2021). For this reason, an innovative concept that combines the aspects of station-based and definable user groups is particularly promising. These findings have not gone unnoticed in the industry. For instance, the widely known shared micromobility platform Spin announced in June 2022 that it will invest up to $2 million in a partnership with Michigan State University and the University of Utah to optimize traffic outcomes in campus environments (Spin, 2022). Similar to Spin, its market competitor Lime has been working with the city of Boulder and the University of Colorado since August 2021 to establish a closed-campus e-scooter sharing service to offer employees, students, and community members an alternative to private cars (City of Boulder, 2022). As described in the first paragraph of the introduction, the main task of marketing is to facilitate the exchange between buyers and sellers. Shared mobility is not about sales but about ensuring high usage rates since there is no ownership of the transfer in the sharing economy. Therefore, it is essential for marketing research to understand why people should adopt and use these new kinds of closed-campus micromobility services. Answering the question of how the marketing discipline can contribute to higher and better user acceptance of this new mode of shared mobility is therefore an important task for the further development of the general acceptance of shared micromobility.

3 Research Problems

3.1 The Sharing Economy from the Marketing Perspective

From a business perspective, the overall sharing economy and its application in several industries (like shared mobility) represent an increasing variety of businesses that offer several benefits. In the sharing economy, consumers do not pay for ownership and sole consumption but for temporary access (Kumar et al., 2018). Because shared goods and services are consumed collaboratively and can be provided by the network of consumers, challenges from the marketing and consumer behavior perspectives arise (Eckhardt et al., 2019). For example, in marketer-provided sharing (e.g., commercial car sharing like Zipcar), the marketing and the provision of the sharing exchange are carried out by the platform itself. In peer-provided sharing (e.g., private car sharing Getaround) the exchange is conducted by the peer provider, and marketing is usually performed by the platform. The long-term success of sharing platforms depends largely on attracting people to use the service for the first time and thereafter to retain them, thus securing a critical mass of users (Akhmedova et al., 2020; Kumar et al., 2018). Therefore, to unravel the complexities of these new forms of sharing-based consumption, marketing, and consumer behavior research has paid attention to the adoption, process, and outcomes (Bardhi & Eckhardt, 2012; Perren & Kozinets, 2018; Zervas et al., 2017). But, although reviews of the research field of the sharing economy exist, these reviews are limited for at least two reasons. First, they are not focused narrowly enough, examining the literature on the sharing economy as a whole and thus lacking the focus to adequately address the specific features of marketing and consumer behavior issues (Cheng, 2016; Ryu et al., 2019; Sutherland & Jarrahi, 2018). Second, the existing review on the sharing economy is too narrow in scope, focusing on specific industries or constructs (Cheng & Edwards, 2019; Huurne et al., 2017; Prayag & Ozanne, 2018). Against this background and to address the specific needs of marketing and consumer behavior research in the sharing economy, the first research question seeks to investigate the academic literature landscape at the intersection of marketing and the sharing economy as a whole.

RQ1: How is the sharing economy synthesized and discussed in the marketing literature, in terms of leading research streams and future research directions?

3.2 The Adoption and Usage of Closed-campus Micromobility

The transportation and mobility sector is one of the most prominent but also important areas of application for sharing-based consumption as cities around the world are experiencing a technology-driven paradigm shift (McKinsey & Company, 2017). In this new mobility environment, shared micromobility services are receiving a lot of attention, especially in urban centers (Shaheen et al., 2020), providing many high-profile examples for the entire shared mobility services market (e.g., Spin and Lime). For consumers, shared micromobility is often promoted as a multi-value mobility service (Abduljabbar et al., 2021). These values include economic benefits (e.g., saving money and time), environmental benefits (e.g., more environmentally sustainable than personal vehicles), utilitarian benefits (e.g., more convenient, quick, and safe than walking), and hedonic benefits (e.g., fun and enjoyment). But while shared micromobility and, particularly, the shared use of e-scooters are a rapidly growing global consumer phenomenon, they are also controversial and highly discussed issues (Gössling, 2020; Milakis et al., 2020). On the one hand, they offer many advantages for urban traffic. On the other hand, they are causing problems, like randomly parked vehicles on sidewalks, risky driving behavior, and vandalism (Gössling, 2020; Useche et al., 2022). Closed-campus micromobility services (Shaheen et al., 2020) aim to overcome the limitations of existing public available solutions and are attracting attention in academia and the market. To design, implement, and promote shared micromobility services in closed-campus environments and to ensure high levels of adoption, practitioners and researchers need to understand the decision factors to adopt such shared micromobility services. This problem leads us to define the second research question:

> **RQ2:** What are the main drivers and barriers to the usage of shared micromobility innovations in closed-campus environments?

3.3 Satisfaction and Continuance Intention with Closed-campus Micromobility

In addition to the need of understanding the initial user adoption of an innovation, which is important for the short-term success of new products and services, the long-term viability also depends on the continuity of user behavior (Bhattacherjee, 2001). Therefore, the continuity of user behavior after initial adoption has become a vital topic in marketing and technology adoption research (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). Regarding fostering continuity of user behavior, investigating consumer satisfaction is fundamental (Bhattacherjee, 2001; Bhattacherjee & Lin, 2015). Consumer satisfaction is understood as the overall evaluation of a consumer's consumption experience with products or services over a period of time (Anderson et al., 2004) and is proposed to be one of the major antecedents of continuance intention to use a product or service. Closed-campus micromobility services are deployed in limited areas, such as university or office campuses, and are only available to the respective campus or organization community (e.g., students, and office employees; Shaheen et al., 2020). First services have started to enter the market and promote themselves as "being the best possible partner for cities while building the safest, most equitable, and most sustainable mobility solution for the communities we serve" (e.g., Spin, 2023). As users do not own the vehicle but use it temporarily for individual purposes, the perceived value of such a solution can be potentially manifold (Abduljabbar et al., 2021). In this context, we investigate the main contributors to satisfaction and drivers of continuance intention and, thus, formulate our research question:

> **RQ3:** What are the contributors to satisfaction and drivers of continuance intention to use a closed-campus micromobility solution?

3.4 Longitudinal Effects of User Experience of Closed-campus Micromobility

Nowadays, innovative and new technologies, products, and services continue to emerge and evolve in our changing and demanding economic and social environment (Venkatesh et al., 2021). This continuous advancement in product and service designs also applies to shared micromobility services (Lazarus et al., 2020), characterized as a sensitive and publicly debated issue (Bortoli, 2021; Gössling, 2020; Milakis et al., 2020). Recent research on the acceptance of new technologies, products, and services highlights the need to understand the changing importance of predictors of acceptance depending on user experience and calls for greater examination of temporal aspects in empirical acceptance research (Blut et al., 2021; Venkatesh et al., 2021). Especially in the case of shared micromobility services, people may have already formed an opinion without ever having used such a service. Consequently, users' perceptions might evolve as users gain experience. Moreover, once consumers have adopted and started using shared micromobility services, the consequences on their feelings and perceptions remain unclear (Jie et al., 2021). Following a recent meta-analysis on technology adoption research (Blut et al., 2021), future research would benefit from increased research on outcomes of innovation adoption. Since shared micromobility is hypothesized to be a more sustainable and active mode of transportation, expectations of improvements in subjective well-being are likely (Abduljabbar et al., 2021). However, the direction of the investigation of well-being as a consequence of adoption is not necessarily intuitive, as subjective well-being was mainly analyzed as an influencing factor in adopting new technologies (Attié & Meyer-Waarden, 2022; Dabholkar & Bagozzi, 2002; Davis & Pechmann, 2013; Meyer-Waarden et al., 2021; Meyer-Waarden & Cloarec, 2022; Munzel et al., 2018). Moreover, in the case of closed-campus environments, the provision, and use of shared micromobility services can produce benefits not only for users but also for the relationship with organizations. Organizational identification is the extent to which a person identifies with his organization and understands the use of the organization as meeting self-defined needs (Homburg et al., 2009; Korschun et al., 2014). By providing such services to their users, organizations could positively influence the identification of their organizational members with the organizations. As a conclusion from the points above, we formulate our final research question:

> **RQ4:** What are the outcomes of shared closed-campus micromobility use, and how do consumers' evaluations evolve with increasing user experience?

4 Contributions to Theory

Through our research, we aim to understand how consumers use and interact with sharing-based products and services. In particular, we focus on the highly debated application of shared micromobility services and their specific application in closed campus environments. The study of shared micromobility in closed-campus environments allows us to consider the complexity of this new form of consumption, as mobility decisions affect most people in their daily work and private lives. In particular, the analysis of the existing literature presented in Chapter 1 helps us to identify and define the research questions related to 1) possible factors influencing consumers' initial intention to use such sharing-based mobility services; 2) factors influencing satisfaction and continuance intention; 3) consumers' evaluation of outcomes of using such services and how they develop with increasing user experience; 4) the underpinning theories to the related questions. By examining these issues and answering our research questions, this study contributes to theory in the following ways.

In Chapter 1, we describe a specific picture of the state of marketing and consumer behavior research literature around the overall topic of the overall sharing economy. We conduct a systematic literature review to complement and extend prior reviews by providing a holistic review of theoretical and empirical aspects of marketing and consumer behavior research about the overall sharing economy and by outlining future research directions that support the advancement of the research domain. Therefore, we use the theory–context–characteristics–methodology (TCCM) review protocol (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018). By using this framework, we intend to answer the following questions: which theories have been used to explain consumer behaviors in the sharing economy (e.g., the adoption, exchange process, and outcomes)?; in which contexts (e.g., industries, countries) has the sharing economy been investigated?; which characteristics from the user, exchange, and platform perspective have been studied?; and which methods have been utilized in marketing and consumer behavior research concerning the sharing economy? Thus, we contribute to the literature by providing a systematic and comprehensive foundation on the overall topic, outlining areas of prior scholarship, and highlighting gaps for future research investigations.

In Chapter 2, we examine and assess the initial adoption of shared micromobility innovations in a professional, closed-campus environment. To do so, we built up a field laboratory for shared micromobility at the Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany (see Section 7 of this chapter for a detailed description). Using the field laboratory DHBW Drive as a case study, we analyze not only behavioral intentions but also real use behavior by considering the behavioral data of our study participants who were registered users of DHBW Drive. In doing so, we make a theoretical contribution in the following way. First, we enhance the unified theory of acceptance and use of technology (UTAUT2; Venkatesh et al., 2012), to establish a conceptual model that explains the initial adoption by incorporating context-specific constructs of consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), and from trust-risk theories (Martin & Murphy, 2017; Pavlou, 2003). Because shared micromobility has specific features, consumer perceived value of a closed-campus micromobility service can be multifold. We contribute to the literature as we do a comprehensive investigation of the importance of consumer perceived value dimensions (Holbrook, 1994; Zeithaml, 1988), namely hedonic, utilitarian, environmental, and economic value, for the adoption process of closed-campus micromobility. Second, as we examine closed-campus micromobility in organizational, mostly professional settings, we add a construct specific to the context of professional task situations: perceived task enablement, which is about the provision of work necessities and environment and has its roots in employee enablement (Adler & Borys, 1996; Permana et al., 2015). By providing mobility options for on-campus and off-campus travel, organizations can enable their members to better accomplish their daily tasks. Investigating if and how perceived task enablement can lead to higher acceptance, contributes to a more profound understanding of service adoption in organizational settings. Finally, we contribute from the methodology point of view to the literature on technology adoption research by using real behavioral data (Blut et al., 2021). Based on the behavioral data provided by DHBW Drive, we empirically test the causal relationship between intention to use (declarative survey-measured) and real use (measured with behavioral data), which is rare in the technology acceptance literature and represents an additional and also methodological contribution (Blut et al., 2021).

In Chapter 3, we focus on understanding the antecedents of “continued use” or “continuance intention” to use shared micromobility services (rather than “acceptance” or “initial intention” to use). We again use the field laboratory DHBW Drive as a case study to examine not only the intention to continue use but also its impact on the behavior of continued real use. Accordingly, we theoretically contribute to the literature in the following ways. First, we contribute to transformative consumer research (Davis et al., 2016; Zeng & Botella-Carrubi, 2023) and enhance the expectation-confirmation model (ECM; Bhattacherjee et al., 2012) with the variable of subjective well-being (Diener et al., 1999). By doing so, we highlight the importance of affective perceptions in the form of subjective well-being (Diener et al., 1999) and its effect on satisfaction, and continued use behavior (Bhattacherjee, 2001) in the context of closed-campus micromobility. Furthermore, we enhance the ECM with constructs drawing from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988) to comprehensively investigate their implications for continued use behavior. Shared micromobility services are highlighted because they offer multiple added values to consumers (Abduljabbar et al., 2021; Buehler et al., 2021). With this understanding, we examine the four different consumer perceived value dimensions (namely hedonic, economic, environmental, and utilitarian value) as predictors of subjective well-being and performance expectancy of closed-campus micromobility services. Finally, and similar to the study in Chapter 2, we contribute to the field of marketing and technology adoption research in the literature (Bhattacherjee & Premkumar, 2004; Blut et al., 2021; Venkatesh et al., 2011) by investigating the effect of continuance intention on real continuance use.

Finally, in Chapter 4, we concentrate on understanding the dynamic adoption and outcomes of a closed-campus micromobility service based on short- and long-term user experience. First, we develop a longitudinal model to explain the antecedents and outcomes of closed-campus micromobility adoption based on the unified theory of acceptance and use of technology (UTAUT2, Venkatesh et al. 2012). We extend the UTAUT2 by including context-specific constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), regulatory focus theory (Avnet & Higgins, 2006; Higgins, 1997) explaining next to the utilitarian path of technology adoption an affective promotion orientated path namely through subjective well-being, a key concept in transformative consumer research theories (Diener et al., 1999; Diener & Chan, 2011), and social identity theory (Ashforth & Mael, 1989). Moreover, based on two independent user samples and a two-wave longitudinal study design, we integrate short-term and long-term user experience effects and investigate the changing importance of predictors and outcomes, which is rare or even non-existent in the technology acceptance literature (Taylor & Todd, 1995; Venkatesh et al., 2002).

5 Contributions to Practice

Our research provides managerial insights for managers and organizations seeking to implement shared micromobility in closed-campus environments and for managers working in the broader context of shared mobility innovation.

We focus our empirical work on variables that draw on two well-established theoretical models, the UTAUT2 (Venkatesh et al., 2012) and the ECM (Bhattacherjee, 2001), enhanced with variables from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), enablement theory (Adler & Borys, 1996; Permana et al., 2015), theory of well-being (Diener & Chan, 2011), and social identity theory (Ashforth & Mael, 1989). In the context of consumer-perceived value, we offer insights into the most significant benefits consumers consider when evaluating the utility of shared micromobility services, based on their perceived gains from using them. We investigate different value dimensions relevant to the context, and results should help to inform marketers what and how to promote the diverse benefits of shared micromobility in closed-campus environments. Moreover, we consider the variable of task enablement in our analysis to investigate how the provision of a closed-campus micromobility service can enable users and contribute to their daily duties, tasks, and job work. Results can help to inform practitioners about the benefits of a closed-campus micromobility service concerning the organization's overall performance. For example, if task enablement turns out to be a significant factor in the adoption process, this might be a good argument for promoting benefits in terms of user and organizational performance. Moreover, we investigate users' perceived subjective well-being as an antecedent and outcome of shared micromobility use. The results can offer additional insights concerning user motivations and outcomes.

Furthermore, the results might be relevant for possible customers of closed-campus micromobility services (i.e., universities, office campuses), and policymakers who are interested in improving the quality of life of their organizational members and residents. Previous research suggests that shared micromobility, and shared mobility in general, can contribute to health and well-being (Eccarius et al., 2021; Milakis et al., 2020). Our results should offer empirical insights into whether this perception also occurs from the user perspective of a closed-campus micromobility innovation. Moreover, we include the variable organizational identification, drawn from social identity theory (Ashforth & Mael, 1989), to investigate the effects of shared micromobility use on the identification with the providing organization. To implement and provide a closed-campus micromobility service sustainably and in the long term, an organization must see enduring added values for its users and itself. In the first step, an organization will weigh the directly measurable benefits (e.g., performance expectancy) against the potential costs and decide whether a closed-campus micromobility solution is profitable. Organizations should, however, also see indirectly measurable benefits in terms of organizational branding. Providing a shared micromobility service to the organizational community can create an investment to differentiate the organization from the competition. Hence, addressing benefits and outcomes for organizations for which such a service would be useful and feasible, can help increase the willingness of organizations to provide such a service to its organizational members.

Finally, the investigation of longitudinal effects in Chapter 4 can provide additional insights for marketers and practitioners. The more consumers experience the benefits of a shared micromobility service, the more they might get confident about the service's ability to serve as an appropriate and effective alternative to current transportation modes. Understanding how consumer evaluations evolve with user experience from test and use experience should contribute to a more profound understanding of when and how promotion should be structured.

6 Dissertation Overview

The thesis consists of four main chapters (see Figure 2). The first chapter presents a systematic literature review of 88 peer-reviewed articles on the sharing economy in marketing and consumer behavior research. Here we propose a research agenda for future research and guide our research questions for the next chapters. Chapters 2, 3, and 4 are empirical studies in the context of closed-campus micromobility, using DHBW Drive as a case study. The second chapter includes an investigation of the initial adoption of shared micromobility innovations in closed-campus settings with registered users of DHBW Drive. The third chapter focuses on the satisfaction and continuity behavior of registered users of DHBW Drive. The fourth chapter focuses on the longitudinal effects of user experience on perceptions of predictors and outcomes of shared micromobility innovations. To investigate the longitudinal effects of short-term and long-term user experience, we replicate the study with two independent samples. One external sample of not-registered users of DHBW Drive (short-term experience) and one internal sample of registered users of DHBW Drive (long-term experience). Finally, we present the conclusion, in which we discuss the theoretical, methodological, managerial, and societal contributions, limitations of our research, and future research directions.

Figure 2: Overview of the Thesis

INTRODUCTION

Chapter 1.
A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Conference:
Schwing, M. (2023). Marketing in the Peer-to-peer Sharing Economy - a Systematic Literature Review. **2023 Academy of Marketing Science Annual Conference**, New Orleans (LA), US, May 17-19.
Targeted journal: Recherche et Applications en Marketing

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Conference:
Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2022). Lime, Bird or Campus Drive? Where Institutions can be ahead of Markets - An Empirical Study about Consumers' Intention to use Closed-campus Micromobility. **2022 Academy of Marketing Science Annual Conference**, Monterey Bay (CA), US, May 25-27.
Targeted journal: Journal of the Association for Information Systems

Chapter 3.
Satisfaction and Continuance Intention with Closed-campus Micromobility

Conference:
Schwing, M. (2022). E-Scooters, Perceived Value and Users' Subjective Well-Being: An Empirical Study about Organization-based Shared Micromobility. **2022 American Marketing Association Summer Academic Conference**, Chicago (IL), US + Virtual. August 12-14.
Targeted journal: Transportation Research Part F: Traffic Psychology and Behaviour

Chapter 4.
Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Conferences:
Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2022). How E-Scooters enhance Identification with your Organization? An Empirical Study about Closed-campus Micromobility Innovations. **AU Virtual International Conference 2022 on "Entrepreneurship & Sustainability in Digital Era"**, Virtual, October 21.
Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2023). Understanding the Dynamic Adoption and Outcomes of Shared Micromobility - a Longitudinal Study based on User Experience. **2023 Academy of Marketing Science Annual Conference, New Orleans (LA)**, US, May 17-19.
Targeted journal: Journal of the Academy of Marketing Science

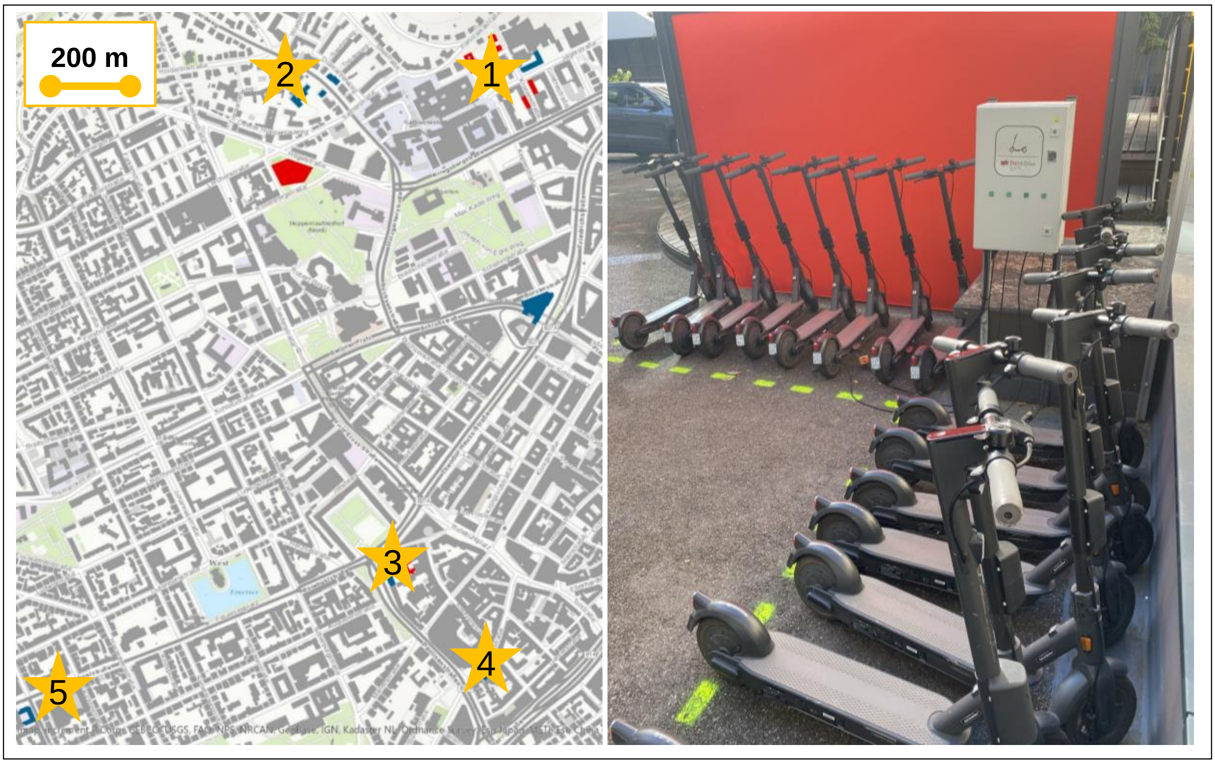
CONCLUSION

7 DHBW Drive – a Field Laboratory for Closed-campus Micromobility

As part of the underlying thesis and to investigate the adoption process of closed-campus micromobility (Chapters 2, 3, and 4), we built up a field laboratory for shared micromobility, named "DHBW Drive", at the Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany. The field laboratory was a joint project with two industry partners (EAR Innohub, 2021; MIMO drive, 2021) and was operated by DHBW University from October 2020 to February 2022. To the best of our knowledge, DHBW Drive represents the first successfully implemented field laboratory for micromobility sharing in a closed-campus environment of a German university.

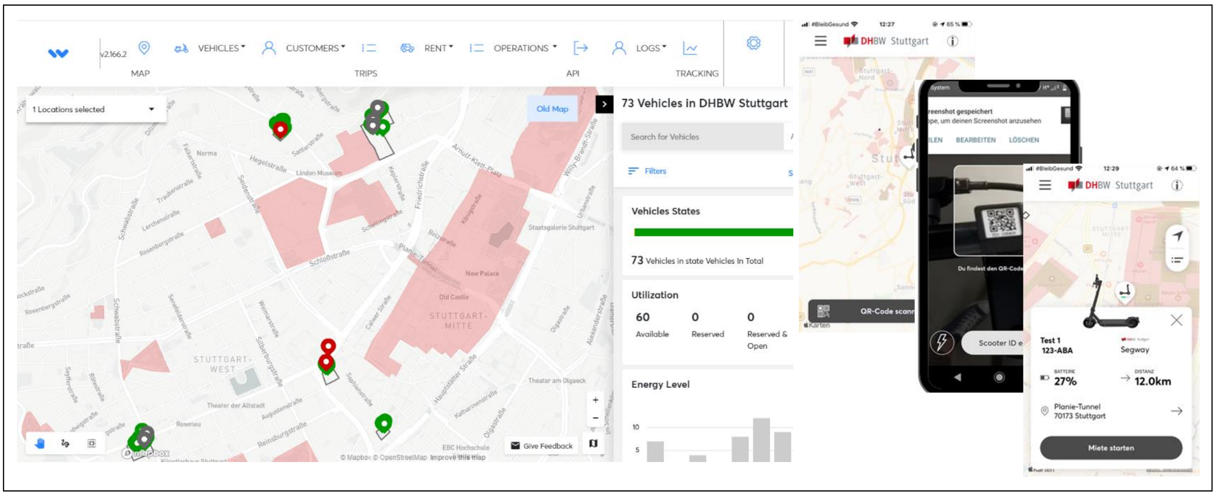
The DHBW University in Stuttgart was a well-suited pilot to study closed-campus micromobility because of at least two reasons. First, Stuttgart is one of the German cities that struggles the most with environmental and traffic problems, due to its basin topology and an increased volume of commuters (e.g., fine particulate pollution; The Guardian, 2017). Second, the DHBW University is not a single-site university with one large campus but is spread across several addresses and buildings in downtown Stuttgart. Through the provision of the service DHBW Drive, all members of the university (approx. 7,000 students and 400 staff) could move between five DHBW sites (GPS-based mobility hubs; average distance 1,500 meters; see the left side of Figure 3) in downtown Stuttgart. In total, 70 e-scooters were free-of-charge available and could be rented at the mobility hubs where the e-scooters were stored and charged using an in-house developed charging concept (see right side of Figure 3).

Figure 3: Location Map and Mobility Hub of DHBW Drive



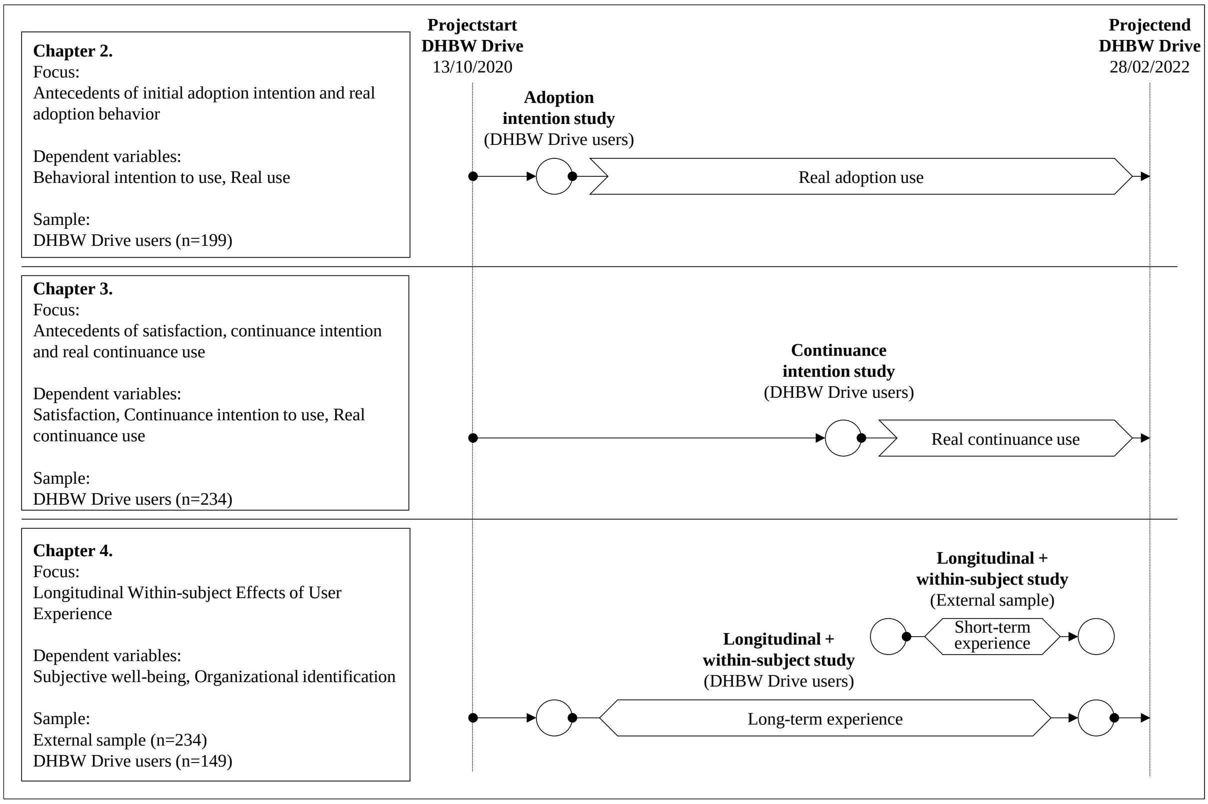
To access and use the service, members of the university had to download an app, which was available for Android and iOS Smartphones, and had to register for the service using their university email. The app was based on a platform software for shared mobility services (Wunder Mobility, 2021) and was customized for the specific needs of the station-based and closed-campus setting of DHBW Drive (see right side of Figure 4). For example, users could only start and end a trip within the predefined GPS-based mobility hubs, and had to take a photo at the end of the trip to ensure that the e-scooters were stored correctly. Moreover, the project team had access to the backend system of the platform to operate the fleet. For example, the backend system provided dashboard functionality to control the booking process (see the left side of Figure 4) and allowed the export of behavioral data such as user booking history.

Figure 4: Screenshots of the Backend and Frontend of DHBW Drive



Over the duration of the operation period, October 2020 to February 2022, more than 2,200 members of the university registered to the service (with a share of 95% of students), more than 12,200 bookings were made, and a total of more than 38,600 km were traveled. In addition to the behavioral data collected through the use of the service, DHBW Drive was the basis for the empirical survey-based studies in Chapters 2, 3, and 4 (see Figure 5). Hereby, the focus of Chapter 2 is to investigate antecedents of initial adoption intention and real adoption behavior of registered users of DHBW Drive. In contrast, Chapter 3 focuses on the satisfaction and continuity behavior of registered users of DHBW Drive. Finally, Chapter 4 is a longitudinal, within-subject study design study and focuses on the effects of user experience on perceptions of predictors and outcomes of adoption behavior over time. For instance, Chapter 4 analyzes the effects of short-term and long-term experience by examining not only an internal sample of registered users of DHBW Drive (long-term experience) but also an external sample of non-registered users of DHBW Drive (short-term experience).

Figure 5: Empirical Studies conducted with DHBW Drive



8 Declaration of Contributions

Chapter 1: This chapter is a joint work with Pr. Lars Meyer-Waarden (Toulouse Capitole University) and Pr. Marc Kuhn (Baden-Wuerttemberg Cooperative State University Stuttgart). The author conducted most of the work for this chapter.

Chapter 2: This chapter is a joint work with Pr. Lars Meyer-Waarden (Toulouse Capitole University) and Pr. Marc Kuhn (Baden-Wuerttemberg Cooperative State University Stuttgart). The author conducted most of the work for this chapter.

Chapter 3: The author independently wrote this chapter.

Chapter 4: This chapter is a joint work with Pr. Lars Meyer-Waarden (Toulouse Capitole University) and Pr. Marc Kuhn (Baden-Wuerttemberg Cooperative State University Stuttgart). The author conducted most of the work for this chapter.

Introduction

Chapter 1.
A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Chapter 3.
Satisfaction and Continuance Intention with Closed-campus Micromobility

Chapter 4.
Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Conclusion

Chapter 1.

A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Abstract

The success of businesses in the sharing economy depends on building and retaining a critical mass of users (Kumar et al., 2018; Laczko et al., 2019), and understanding users' motivations, barriers, and outcomes is an important marketing task. To help unravel the complexities of these new forms of exchange, consumer behavior and marketing research has paid attention to the adoption, sharing process, and outcomes of sharing exchange in the last decade, both from user and business perspectives. However, a holistic view of the accumulated knowledge is sparse. This study reviews 88 articles using the theory-context-characteristics-methodology (TCCM) framework protocol (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018) to paint a comprehensive and precise picture of the field and to develop a future research agenda. By using this framework, we intend to answer the following questions: what theories have been used to explain consumer behaviors in the sharing economy (e.g., the adoption, sharing process, and outcomes)?; in what contexts (e.g., industries, countries) has research been investigated?; what characteristics from the user, exchange, and platform perspective have been studied?; and what methods have been utilized in marketing and consumer behavior research? Our review reveals an existing focus on user- and exchange-

related theories. While there is many research on accommodation sharing and ride sharing (as Airbnb and Uber are the most popular past examples), we identified contribution gaps for more recent applications (e.g., micromobility sharing). Regarding investigated characteristics, we see little empirical research from a non-user perspective and research would contribute by studying not only behavioral intentions but also real use and possible outcomes. This, in turn, opens up chances from a methodological perspective. For instance, literature would contribute from investigating more real-world behavioral and longitudinal data to increase the validity of further insights.

Figure 6: Chapter 1 – Objectives, Methodology, and Publications

OBJECTIVES	• Investigate the academic literature landscape at the intersection of marketing and the sharing economy (Eckhardt et al., 2019) • Providing a holistic overview of theoretical and empirical aspects of marketing and consumer behavior research (Palmatier et al., 2018) • Derive areas of future research directions (Snyder, 2019; Vrontis & Christofi, 2019)
METHODOLOGY	• Systematic literature review based on TCCM (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018) • 88 articles from the marketing and consumer behavior research field (Baumgartner & Pieters, 2003; Hult et al., 2009; Theoharakis & Hirst, 2002)
PUBLICATIONS	Schwing, M. (2023). Marketing in the Peer-to-peer Sharing Economy - a Systematic Literature Review. 2023 Academy of Marketing Science Annual Conference, New Orleans (LA), US, May 17-19. Targeted Journal: Recherche et Applications en Marketing

1 Introduction

A core task of marketing is to facilitate exchange between buyers and sellers that traditionally has involved the permanent transfer of ownership from the seller to the buyer (Bagozzi, 1974). In the recent past, several drivers, such as developments in information and communications technology, growing consumer awareness, and anti-materialism consumer behavior (Albinsson et al., 2019; Botsman & Rogers, 2010; Hamari et al., 2016), have shaped new forms of exchange that challenge the classical way marketing operates to facilitate exchange. The sharing economy (SE) represents a steadily growing part of our global economy, in which people can consume without having to buy and own. It has disrupted many well-established industries, such as the hotel and taxi industries, by offering low-cost consumption options without the responsibility of ownership (Eckhardt & Bardhi, 2015; Kumar et al., 2018). For example, a total of 45 million adults in the United States used sharing economy services in 2016, and this number is expected to increase to 86 million by the end of 2021 (Statista, 2021); thus, the global market size of the entire sharing economy was estimated at $15 billion in 2015 and is expected to grow to $335 billion by 2025 (PwC, 2015, 2018).

Parallel to this rise of new market-disrupting sharing-based consumption modes, the sharing economy has increasingly attracted attention in research in the last decade, both within and outside the marketing domain. From an academic standpoint, the sharing economy is described as a form of exchange that does not involve the transfer of ownership and is mediated via online platforms. Within this form of mediated exchange, many alterations can be found, and research has used a variety of names to refer to these practices, including access-based consumption (Bardhi & Eckhardt, 2012), commercial sharing systems (Lamberton & Rose, 2012), lateral exchange markets (Perren & Kozinets, 2018), presumption (Ritzer & Jurgenson, 2010), collaborative consumption (Belk, 2014; Botsman & Rogers, 2010) and peer-to-peer sharing (Benjaafar et al., 2019; Gupta et al., 2019; Stofberg & Bridoux, 2019; Wirtz et al., 2019).

From a business perspective, the SE represents an increasing variety of platform businesses that offer several benefits, such as cost-effective consumption and optimized usage of underutilized assets. In recent years, the SE has brought forth well-known and successful companies, such as Airbnb, BlaBlaCar, and Uber. As users can behave as both consumers and providers (and vice versa), shared goods and services can be provided and consumed by the network itself. In this regard, peer-provided sharing is different from marketer-provided sharing: in marketer-provided sharing, the marketing, and the provision of the sharing exchange are carried out by the platform itself. In peer-provided sharing, the sharing exchange is conducted by the peer provider, and the marketing is done by the platform. The platform must serve two different user sides and can only indirectly influence service quality as well as consumer behavior. Additionally, in peer-provided sharing, one side of the market depends on the availability of the other, since neither side of the platform would be able to participate without the existence of the other (Benjaafar et al., 2019; Hagiu, 2014; Rochet & Tirole, 2003). To facilitate exchange, it is crucial to understand the motives, barriers, and outcomes for consumers as well as for providers (Ertz et al., 2017; Milanova & Maas, 2017).

To help unravel the complexities of these new forms of exchange, consumer behavior and marketing research has paid attention to the adoption, sharing process, and outcomes of SE exchange in the last decade, both from user and platform perspectives. Although reviews of the research field of the sharing economy exist, prior reviews are limited for at least two reasons. First, existing reviews are not narrow enough, as they do not have the necessary focus to sufficiently consider the specific characteristics of marketing and consumer behavior (Cheng, 2016; Cheng & Edwards, 2019; Huurne et al., 2017; Matzler et al., 2015; Ryu et al., 2019; Sutherland & Jarrahi, 2018). For example, Sutherland and Jarrahi (2018) reviewed 435 publications on the sharing economy and related terms like digital platforms and identified the main trends in the literature. Specifically, they draw a set of essential advances in sharing economy technologies and organize the literature around the concept of platform mediation. Second, existing reviews are too narrow as they focus on specific industries or constructs. For example, Prayag and Ozanne (2018) reviewed academic research on peer-to-peer accommodation sharing over the period from 2010 to 2016 and identified seven key themes for the current regime in the accommodation sector. To understand how the trust of users in the sharing economy is influenced, Huurne et al. (2017) performed a systematic literature review and analyzed 45 articles. However, only nine articles specifically studied consumer behavior concerning trust in the context of the sharing economy and 36 were performed in the context of customer-to-customer (C2C) e-commerce.

Against this background, our systematic review strives to complement and extend prior reviews by providing a more holistic review of theoretical and empirical aspects of marketing and consumer behavior research about the SE and by outlining future research directions that support the advancement of the marketing and consumer behavior research domain. Therefore, we use the theory-context-characteristics-methodology (TCCM) review protocol (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018). By using this framework, we intend to answer the following questions: what theories have been used to explain consumer behaviors in the SE (e.g., the adoption, sharing process, and outcomes)?; in what contexts (e.g., industries, countries) has research investigated?; what characteristics from the user, exchange, and platform perspective have been studied?; and what methods have been utilized to study the SE in marketing and consumer behavior research?

We contribute to the marketing and consumer behavior literature on the SE in multiple ways. To begin with, our review paints a specific picture of the state of marketing and consumer behavior research. In total, we review 88 articles concerning key theoretical and empirical characteristics. Following the TCCM protocol, our review shows that research is still in its infancy, having recently started. The analyzed studies rely on a wide range of single theories, examining and testing psychological processes that are user-related and exchange-related. Most SE research is set in developed Western countries and focuses on only a small set of industries, dominated by the accommodation and mobility sector. Our detailed investigation of analyzed characteristics reveals that SE research has focused on user-related and exchange-related variables, whereas platform-related and other groups of variables (i.e., industry and country) play a minor role. A wide range of methods has been used to analyze. Because of the research domain's novelty, we found many qualitative and conceptual studies in addition to the dominant quantitative research, resulting in various methods.

Second, based on lessons learned and evolving directions, we provide a future research agenda about the SE that outlines several themes based on the TCCM structure. For the theory side, we suggest the use of theories that better account for the specific setting of the SE and multiple perspectives of sharing exchange. In particular, theories that incorporate the platform as a central intermediary could enhance future studies to explore platform influences on user beliefs and behavior, a major gap in SE research. For the context side, we see that much research has been carried out on accommodation and ride sharing, which represent the most prominent examples from practice in the last years. However, the market is continuously evolving (e.g., shared micromobility in the transportation sector), and sharing services can be found in many sectors. Thus, research in new and other contexts would lead to more in-depth insights and can enhance future consumer behavior research. Finally, platform-related outcomes have so far received little research attention and should be taken into greater consideration by marketing and consumer behavior research.

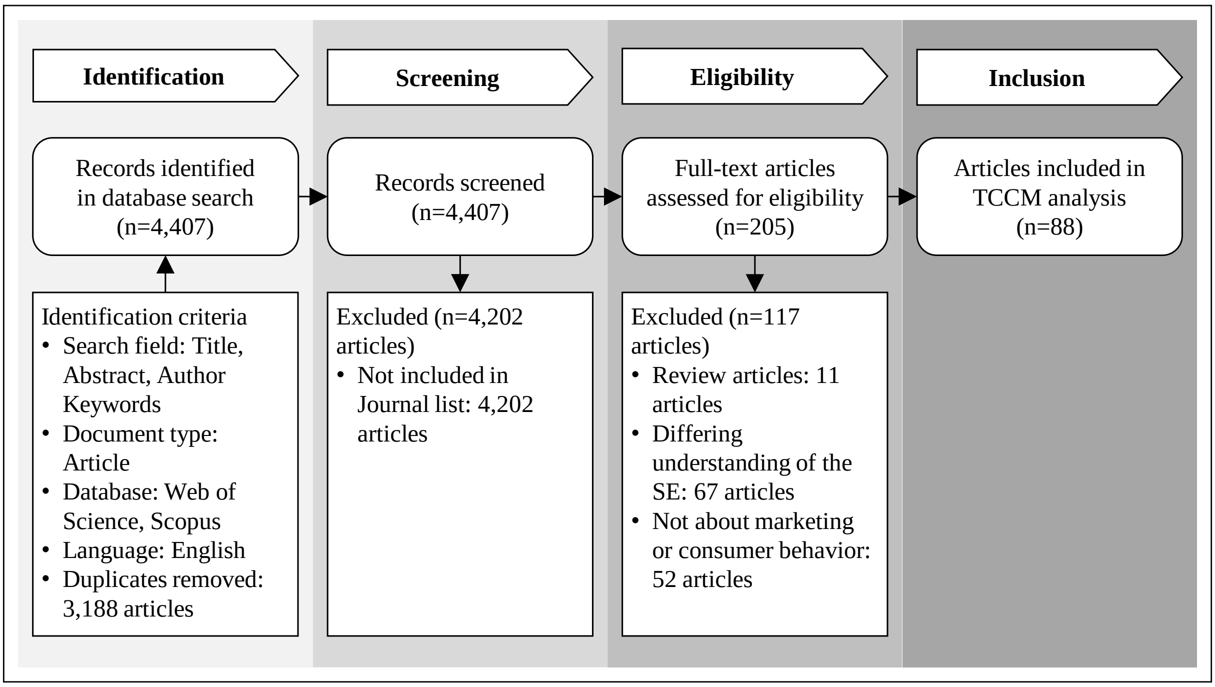
In the following sections, we first introduce our review approach. Second, we provide a general overview of consumer behavior and marketing research on SE. Third, we discuss the theoretical perspectives incorporated by marketing and consumer behavior research to explain the SE. We then describe the investigated contexts, incorporated variables, and methods used in research. Finally, we address research gaps and provide directions for future research that help advance the research field.

2 Review Approach

Review papers are, in their most general form, critical evaluations of material that has already been published and either involve quantitative estimations (i.e., meta-analysis) or not (i.e., systematic reviews; Bem, 1995; Palmatier et al., 2018). Systematic reviews aim to identify, examine and synthesize evidence from prior research (Hulland & Houston, 2020; Paul & Criado, 2020) to provide an integrated overview of the current state of knowledge (Palmatier et al., 2018, p. 2) and derive future research directions (Snyder, 2019; Vrontis & Christofi, 2019). Therefore, systematic literature reviews are traditionally further classified as domain-based, theory-based, and method-based (Palmatier et al., 2018; Paul & Criado, 2020). Domain-based reviews focus on reviewing, synthesizing, and extending a body of literature in the same substantive domain, theory-based reviews analyze a body of literature that uses the same underlying theory and method-based reviews focus on literature that facilitates the same underlying method (Palmatier et al., 2018; Paul & Criado, 2020). Domain-based reviews can be further differentiated into structured, framework-based, bibliometric, hybrid and those aiming for theory development (Paul & Criado, 2020, p. 2). In line with our research objectives, that is, to analyze marketing and consumer behavior research about the SE, we adopt the framework-based review approach theory-context-characteristics-methodology (TCCM; Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018). The main advantage of the TCCM approach is that it is more holistic, sheds light on both theoretical and empirical aspects of a specific research domain, shows a more robust and acceptable structure, and overcomes the limitations of narrow reviews (Paul et al., 2021; Paul & Criado, 2020).

All types of reviews require eligibility criteria from journal selection to article identification (Snyder, 2019). To make our systematic literature search as transparent and traceable as possible, we adopt the PRISMA approach (Preferred Reporting Items for Systematic reviews and Meta-Analyses; Liberati et al., 2009), which has been used for recent reviews in management science (e.g., Sprong et al., 2021). Our PRISMA approach is divided into four phases (identification, screening, eligibility, and inclusion) and was evaluated by scientists who focus on the SE and related subject areas before execution (see Figure 7).

Figure 7: Systematic Literature Search Process (adapted from Liberati et al., 2009)



First, we conducted an extensive keyword search in two databases, Web of Science and Scopus (Chadegani et al., 2013; Meho & Yang, 2007). As highlighted in the introduction, the SE is understood as an umbrella concept that encompasses a multitude of different, sometimes conflicting concepts (Gerwe & Silva, 2020; Schlagwein et al., 2020). To minimize the risk of missing relevant articles in the screening phase, we developed a search string with many similar terms in the context of the SE. We applied the following search string for the titles, keywords, or abstracts of journal articles in the English language: *"sharing economy" OR "share economy"*

OR “access-based consumption” OR “access-based services” OR “product service systems” OR “collaborative consumption” OR “collaborative economy“ OR “gig economy” OR “lateral exchange market” OR “peer-to-peer sharing“ OR “peer-to-peer economy”.* This search yielded a total of 4,407 records after duplicates were removed.

Second, the records were screened regarding their relevance to marketing and consumer behavior literature. We adopted practices from Morgan et al. (2018) to guarantee representativeness, completeness, and high quality for our review and only included articles from the most influential marketing and management journals. Therefore, we used a selection approach that has been used in prior reviews (e.g., Katsikeas et al., 2016; Lehmann et al., 2006; Morgan et al., 2018) and combined three different journal ratings (Baumgartner & Pieters, 2003; Hult et al., 2009; Theoharakis & Hirst, 2002) to select the most influential journals in our research field. The resulting list of journals includes *Journal of Marketing, Journal of Marketing Research, Journal of Consumer Research, Marketing Science, Journal of the Academy of Marketing Science, Management Science, Journal of Consumer Psychology, Journal of International Business Studies, Journal of Retailing, International Journal of Research in Marketing, Journal of Service Research, Journal of Product Innovation Management, Harvard Business Review, Marketing Letters, Journal of Business Research, MIT Sloan Management Review, Journal of Advertising, European Journal of Marketing, Psychology & Marketing, Journal of Public Policy & Marketing, Journal of Advertising Research, Industrial Marketing Management, California Management Review, Journal of International Marketing, Journal of Interactive Marketing, International Marketing Review, Journal of Business Ethics, Quantitative Marketing and Economics, Decision Sciences, Journal of Marketing Management, International Journal of Market Research, Journal of Business-to-Business Marketing, Journal of Business & Industrial Marketing, Journal of Economic Psychology, Journal of Services Marketing, Business Horizons, Journal of Consumer Affairs,* *Journal of Business Logistics, Journal of Marketing Theory & Practice, Journal of Consumer Marketing, International Journal of Consumer Studies, Journal of Brand Management, Journal of Consumer Behaviour, Journal of Retailing and Consumer Services, and Journal of Strategic Marketing.* This yielded a total of 205 articles.

Third, we checked all 205 articles' full texts for eligibility, applying the following criteria in the screening phase. Articles that did fit into one of the following categories were screened out: 1) meta-analyses or review papers, 2) articles with a differing understanding of the SE (e.g., some articles understand second-hand selling platforms as a concept of the SE; Parguel et al., 2017), 3) articles not focusing on questions relevant to marketing and consumer behavior (e.g., articles that analyze the impact of SE on the established industries; Weber et al., 2019). Finally, our analysis included 88 articles published in 30 journals (see Table 1).

Table 1: Sampled Publications of SE Marketing Research by Journal

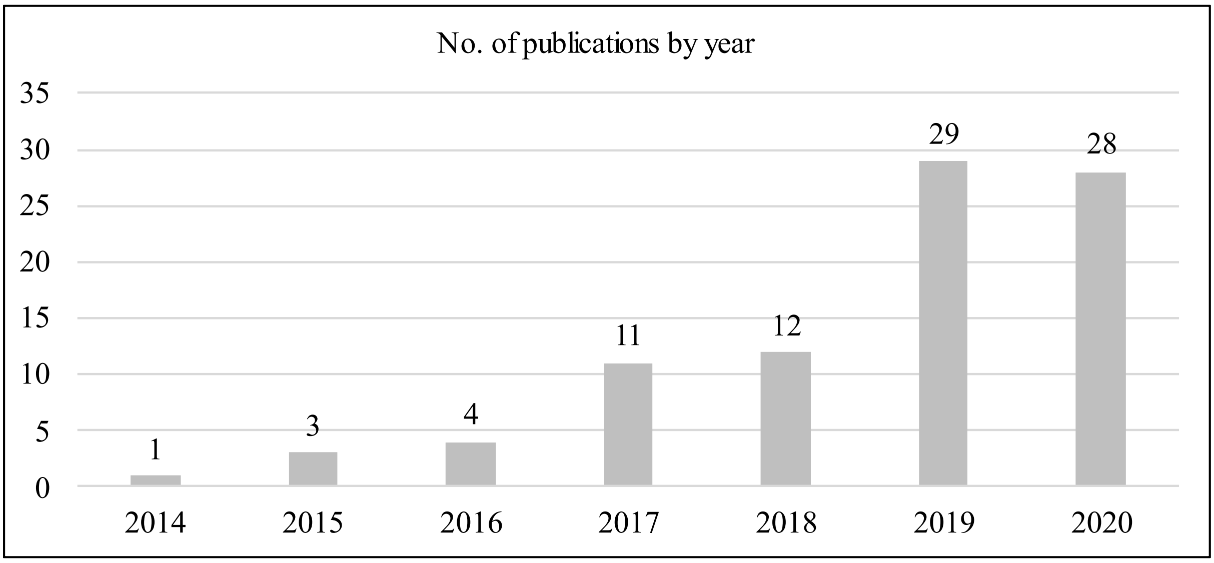
Publications	**No. of articles**	**%**	**Articles**
Journal of Business Research	13	14.8	Akbar (2019); Akhmedova et al. (2020); Belk (2014); Benoit et al. (2017); Davidson et al. (2018); Gleim et al. (2019); Gupta et al. (2019); Hartl et al. (2016); Lu et al. (2020); Lutz and Newlands (2018);Milanova and Maas (2017) Pies et al. (2020); Roos and Hahn (2017)
Journal of Consumer Marketing	8	9.1	Barbosa and Fonseca (2019); Ertz et al. (2018); Frechette et al. (2020); Hwang and Griffiths (2017); Li and Atkinson (2020); Mittendorf (2018); Perren et al. (2019) Zhang (2019)
Journal of Business Ethics	6	6.8	Etzioni (2019); Ma et al. (2020); Mercier-Roy and Mailhot (2019); Roos and Hahn (2019); Vith et al. (2019); Wruk et al. (2019)
Psychology & Marketing	6	6.8	Buhalis et al. (2020); Ert and Fleischer (2020); Hartl et al. (2020); Mai et al. (2020); Pantano and Stylos (2020); Stofberg and Bridoux (2019)
Journal of Services Marketing	5	5.7	Guillemot and Privat (2019); Guyader (2018); Hofmann et al. (2017); Oyedele and Simpson (2018); Yang et al. (2017)

Journal of Marketing Theory & Practice	5	5.7	Albinsson et al. (2019); Griffiths et al. (2019); Ozbal et al. (2020); Philip et al. (2019); Suri et al. (2019)
Journal of Retailing and Consumer Services	4	4.5	Del Alonso-Almeida et al. (2020); Lindblom et al. (2018); Park and Armstrong (2019a); Park and Armstrong (2019b)
Industrial Marketing Management	3	3.4	Harvey et al. (2020); Kumar et al. (2018); Laczko et al. (2019)
Journal of Marketing	3	3.4	Costello and Reczek (2020); Eckhardt et al. (2019); Perren and Kozinets (2018)
Journal of Consumer Affairs	3	3.4	Balderjahn et al. (2020); Seegebarth et al. (2016); Shepherd and Matherly (2020)
Journal of Service Research	3	3.4	Fritze et al. (2020); Hazée et al. (2019); Lin et al. (2019)
Journal of Consumer Behaviour	3	3.4	Liu et al. (2020); Möhlmann (2015); Neunhoeffer and Teubner (2018)
Management Science	3	3.4	Benjaafar et al. (2019); Burtch et al. (2018); Jiang and Tian (2018)
International Journal of Consumer Studies	3	3.4	Berg et al. (2020); Kim and Jin (2020); Tunçel and Özkan Tektaş (2020)
International Journal of Market Research	2	2.3	Arteaga-Sánchez et al. (2020); Ertz et al. (2017)
Journal of Interactive Marketing	2	2.3	Pera et al. (2016); Rangaswamy et al. (2020)
Business Horizons	2	2.3	Habibi et al. (2017); Wilhelms et al. (2017)
Journal of Consumer Research	2	2.3	Aspara and Wittkowski (2019); Scaraboto (2015)
Journal of Strategic Marketing	1	1.1	Cheah et al. (2020)
Journal of International Marketing	1	1.1	Steenkamp (2020)
California Management Review	1	1.1	Apte and Davis (2019)
Journal of Marketing Management	1	1.1	Philip et al. (2015)
Journal of Economic Psychology	1	1.1	Jaeger et al. (2019)
Journal of Marketing Research	1	1.1	Zervas et al. (2017)
Journal of the Academy of Marketing Science	1	1.1	Dellaert (2019)
Journal of Brand Management	1	1.1	Schivinski et al. (2020)
MIT Sloan Management Review	1	1.1	Matzler et al. (2015)
European Journal of Marketing	1	1.1	Caldwell et al. (2020)
International Journal of Research in Marketing	1	1.1	Gielens and Steenkamp (2019)

Journal of Business Logistics	1	1.1	Carbone et al. (2017)
Total	88	100	

Among the 30 included marketing and consumer behavior journals, 16 are ranked as 2021 AJG (Association of Business Schools) 4*, 4, or 3 and include 48 articles (54.4%). This highlights the high relevance and importance of SE research for the marketing and consumer behavior research domain. As SE is still a young research field and consumer behavior and marketing research is limited, we decided to include all works published, despite the lower ranking of the 14 remaining journals (2021 AJG Ranking of 2 and 1). Figure 8 plots the number of publications over time and illustrates the continuous and growing scholarly interest in this topic, further underscoring the relevance of a systematic review of existing publications and marketing and consumer behavior research on SE.

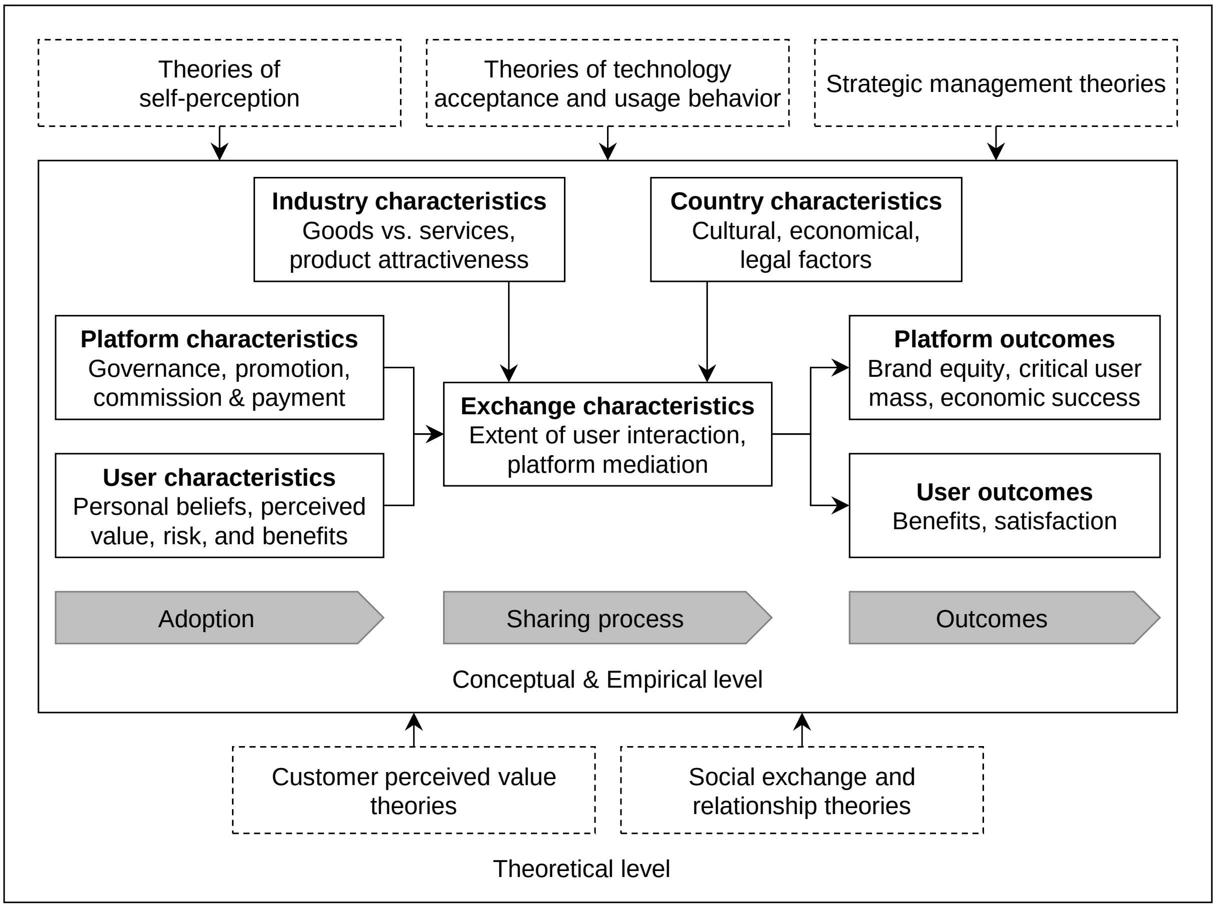
Figure 8: Number of Publications on SE Marketing Research by Year



3 General Overview

The marketing and consumer behavior literature on the SE addresses aspects that determine adoption, the sharing process, and outcomes, both from user and platform perspectives. To visualize existing knowledge and research, we developed a framework of SE research that provides a general overview (see Figure 9). The theoretical level shows the main theories that support the conceptual models that are developed or tested at the conceptual and empirical levels. The conceptual and empirical levels can be structured along two dimensions: first, SE research can be described based on the stages to which it relates, i.e., adoption, sharing process, and outcomes; and second, we distinguish the SE research based on the entity level to which the investigated characteristics relate. Some studies examine characteristics at the user level (e.g., user beliefs, perceived value, risk, and benefits), while others incorporate constructs at the exchange level (e.g., user platform relationship interaction), platform level (e.g., platform governance), industry level (e.g., product characteristics), and country level (e.g., cultural and legal factors). Figure 9 illustrates this structure and links various levels and stages of analysis.

Figure 9: Framework of SE Marketing Research



In the following sections, we use the TCCM framework to systematically review and analyze the literature. First, we review the theoretical foundations that are most frequently used in SE research. Second, we discuss the conceptual and empirical domain of SE research starting with an investigation of different contexts, i.e., business context and perspective, industry, and country. Third, we analyze the characteristics related to the different entity levels (e.g., user, platform, exchange) that have to be considered during the adoption, sharing process, and outcome stages. In particular, we outline the independent, mediating, moderating, and dependent variables that have been studied. Fourth, and finally, we evaluate methodological aspects, including the research approach, data types, and analytical methods that have been used to study the SE. Based on this systematic review, we provide a comprehensive agenda for future research following the same structure.

4 Theory

The term theory can be interpreted in several ways (Abend, 2008; Wacker, 1998). In a theoretical context, the term theory is often used to explain a particular social phenomenon and to describe a general proposition, or logically connected system of general propositions, which establishes a relationship between two or more variables (Abend, 2008). For our research, we adopt this interpretation and understand theories as reasoned statements to describe social phenomena and how a set of relevant characteristics (e.g., consumer characteristics) are related to each other to explain and forecast empirical occurrences (Anderson & Rudner, 1968; Hunt, 2002). Our analysis of publications in marketing and consumer behavior research reveals many theories that have been used to analyze and explain the complex relationships and processes between users and platforms. In terms of the theories utilized, we observe that only 12 articles (13.6%) draw on multiple theories, most studies use one underlying theory (42 articles, 47.7%), and 34 articles do not refer to any specific theory or framework (38.6%). However, most of the articles without underlying theories involve conceptual or qualitative research, and only 14 articles without underlying theories involve quantitative research methods (15.9%). Table 2 provides an overview of the main theories used in consumer behavior and marketing research on the SE. These theories can be broadly classified into seven clusters, depending on their similarity in terms of the variables they assume to study, the effects, and the context in which they are applied, i.e., social exchange and relationship theories (18 articles, 20.5%), theories of self-perception (13 articles, 14.7%), Consumer perceived value theories (11 articles, 12.5%), strategic management theories (7 articles, 8.0%), theories of technology acceptance and usage behavior (6 articles, 6.8%), service orientated theories (3 articles, 3.4%) and brand management theories (2 articles, 2.3%). In the following sections, we discuss the most frequently used theory clusters and briefly explain their related theories.

Table 2: Theories employed in SE Marketing Research

Theory cluster	**Exemplary theories**	**No. of articles**	**%**	**Exemplary studies**
Social exchange and relationship theories	Social exchange theory (Emerson, 1976), Theory of trust and power (Luhmann, 1979), Construal level theory (Liberman et al., 2007)	18	20.5	Mittendorf (2018); Liu et al. (2020); Tunçel and Özkan Tektaş (2020)
Theories of self-perception	Extended self theory (Belk, 1988), Cross-cultural theory (Hofstede, 1980)	13	14.8	Frechette et al. (2020);Del Alonso-Almeida et al. (2020); Hartl et al. (2020)
Consumer perceived value theories	Consumers' perceived value (Holbrook, 1994), Theory of consumption values (Sheth et al., 1991), Value-belief-norm theory (Stern et al., 1999)	11	12.5	Ertz et al. (2017); Balderjahn et al. (2020); Roos and Hahn (2017)
Theories of technology acceptance and usage behavior	Theory of planned behavior (Ajzen, 1991), Social cognitive theory (Bandura, 1989)	6	6.8	Roos and Hahn (2019); Arteaga-Sánchez et al. (2020); Lindblom et al. (2018)
Strategic management theories	Capabilities approach (Day, 1994), Institutional theory (Hoffman, 1999), Stakeholder theory (Freeman, 1999)	4	4,6	Benoit et al. (2017); Laczko et al. (2019); Wruk et al. (2019)

Service theories	Service-dominant logic (Vargo & Lusch, 2008), Transformative service research (Anderson et al., 2013), Attribution theory (Weiner, 1972)	3	3.4	Buhalis et al. (2020); Suri et al. (2019)
Brand management theories	Brand equity theory (Faircloth et al., 2001), Consumers' online brand-related activities (Muntinga et al., 2011)	2	2.3	Ozbal et al. (2020); Schivinski et al. (2020)
Other theories	Political theory (Roucek 1943), Theory of emerging adulthood (Arnett, 2000), Performative Theory (Austin, 1962)	3	3.4	Scaraboto (2015); Oyedele and Simpson (2018); Caldwell et al. (2020)
No guiding theory		34	38.6	Milanova and Maas (2017); Guillemot and Privat (2019)

Note: The number of articles amounts to more than 88 because several articles draw on multiple theoretical perspectives (e.g., Fritze et al., 2020; Hartl et al., 2020; Roos & Hahn, 2019). The reported frequencies are based on 88 included articles.

4.1 Social Exchange and Relationship Theories

To understand and analyze the mechanism between users and platforms, research often uses theories that relate to social exchange and relationship processes. The major aim of sharing platforms is to facilitate sharing exchange and to maintain a critical mass of users. Therefore, understanding social exchange and relationships is crucial. To reach this goal, frequently used theories in this theory cluster are social exchange theory (3 articles, 3.4%; Emerson, 1976), theory of trust and power (2 articles, 2.3%; Luhmann, 1979), and construal-level theory (2 articles, 2.3%; Liberman et al., 2007). For example, social exchange theory understands social exchange as "the exchange of activity, tangible or intangible, and more or less rewarding or costly, between at least two persons or more" (Homans, 1961). In addition, the theory states that perceived profits can be both tangible and intangible and that the nature and amount of perceived profits depend on individual user perceptions (Blau, 1964; Emerson, 1976; Homans, 1961). SE exchange is based on an interpersonal exchange of tangible and intangible resources

(Belk, 2010, 2014); therefore, analyzing interpersonal and platform interactions is fundamental. In this context, social exchange theory has been applied to explain the factors that lead to interaction and familiarity with peer users and platforms (Guyader, 2018; Kumar et al., 2018), the antecedents of customer civility (Ma et al., 2020) and the choice of sharing mode (Aspara & Wittkowski, 2019).

Another frequently used theory is the theory of trust and power, which provides a foundation for explaining the prerequisite for trust by creating a suitable framework and understanding of the environment (Luhmann, 1979). This theory understands trust as a collective attribute that is created from interactions between different actors and is key to interpersonal relationships, as it reduces uncertainty. In contrast to trust, power is understood as a mechanism to control the dynamics of social relationships through the use of sanctions. It has been applied to investigate trust in peer users and platforms as antecedents of the intention to use and provide (Mittendorf, 2018) and to analyze sharing forms in terms of trust in platforms (Berg et al., 2020).

In addition to the already mentioned theories, construal-level theory (CLT) is a theory of social psychology that describes the relationship between psychological distance and the extent to which people’s thinking (e.g., about objects and events) is abstract or concrete (Liberman et al., 2007). According to CLT, psychological distance affects consumer decisions and behaviors and is theorized in four dimensions, all of which are embodied in sharing-based consumption: time, space, social distance, and hypotheticality (Tunçel & Özkan Tektaş, 2020). In the context of the SE, CLT has been incorporated to examine how social distance or closeness impacts relationships between users and platforms (i.e., Frechette et al., 2020; Tunçel & Özkan Tektaş, 2020) and to show that open-to-experience users, who feel less social distance from peer users, are more likely to participate.

4.2 Theories of Self-perception

The cluster of theories of self-perception includes frameworks that help to understand users' perceptions of themselves and their personal beliefs. One of the most dominant frameworks to examine personal and cultural differences of users is the cross-cultural theory (4 articles, 4.5%), developed by Hofstede (1980), which examines five dimensions of culture: power distance, uncertainty avoidance, individualism vs. collectivism, masculinity vs. femininity, and long-term vs. short-term orientation. This framework has been used to examine whether cultural dimensions influence user participation in the SE. For example, these studies demonstrate that collectivism (Albinsson et al., 2019; Gupta et al., 2019) and materialism (Albinsson et al., 2019; Davidson et al., 2018) positively affect the intention to rent and provide, whereas uncertainty avoidance has a negative effect (Gupta et al., 2019).

Another frequently used theory in this cluster is the theory of extended self (4 articles, 4.5%). According to Belk (1988), possession and ownership make a significant contribution to our identity and reflect our identity. Therefore, the consumption of a shared object that is not owned can induce possessive perceptions. Psychological ownership refers to a sense of ownership of a particular target, even if there is no legal ownership, and therefore has been examined in several studies. For example, research has shown that psychological ownership can act as a substitute for physical ownership and has a positive influence on sharing usage (Fritze et al., 2020) and that consumers feel happier when they have greater psychological ownership over an item (Li & Atkinson, 2020).

4.3 Consumer Perceived Value Theories

The concept of consumer perceived value has been given many definitions in the marketing literature (Holbrook, 1994; Sheth et al., 1991; Zeithaml, 1988). Perceived value is defined as "the overall assessment of the utility of a product based on perceptions on what is received and what is given” (Zeithaml, 1988, p. 14). Accordingly, value can be understood as the weighting between benefit and cost. Holbrook (1994) understands customer value as an interactive and relativistic preference experience that involves an interaction between an object (e.g., a shared product or service) and a subject (e.g., consumer or provider). This object-subject interaction is relativistic in three dimensions: first, it involves a comparison between objects (comparative); second, it can vary from one person to another (personal); and third, it depends on the situation in which the evaluation takes place (situational). Similar to the definitional understanding, there are also specific terms for customer value categories: functional, social, emotional, epistemic, and conditional (1 article, 1.1%; Sheth et al., 1991); economic, hedonic, social, and altruistic (3 articles, 3.4%; Holbrook, 2006); confidence, special treatment, social and safety (1 article, 1.1%; Hennig-Thurau et al., 2002); or traditional, egoistic and altruistic (2 articles, 2.3%; Stern et al., 1999). All these suggested categories are based on specific contexts. The context of the SE has specific features, as users can take both the consumer and the provider side of the market. The review of studies using consumer perceived value theories shows a wide range of values that have been incorporated, e.g., utilitarian value, hedonic value, and symbolic value (Hwang & Griffiths, 2017); altruistic value, biospheric value, and egoistic value (Roos & Hahn, 2019); utilitarian motivation, experiential motivation, protester motivation, and spiritual motivation (Ertz et al., 2017); and concern-for-sustainability, social, variety-seeking, fun and cost-saving (Kim & Jin, 2020). Research shows that customers’ perceptions of value depend primarily on their personal beliefs and situation (Davidson et al., 2018; Oyedele & Simpson, 2018), the exchange role (Barbosa & Fonseca, 2019; Ertz et al., 2017), and product and service characteristics (Arteaga-Sánchez et al., 2020; Hazée et al., 2019) and that consumer perceived value has differing impacts on attitude towards the sharing process (Hwang & Griffiths, 2017), participation (Davidson et al., 2018), satisfaction, commitment, and loyalty (Li & Atkinson, 2020; Möhlmann, 2015; Yang et al., 2017).

4.4 Theories of Technology Acceptance and Usage Behavior

The cluster of theories of technology acceptance and usage behavior includes frameworks and models that have been used to analyze and predict user acceptance and usage behavior. The theory of planned behavior (TPB) is a psychological theory that links beliefs and behavior and relies on three core components, namely, attitude (reflecting the overall positive or negative evaluation of performing a behavior), subjective norm (which refers to the perceived social pressure from significant others to perform or not perform the behavior), and perceived behavioral control (that refers to the perceived ease or difficulty of performing a behavior), to shape a person’s behavioral intentions (Ajzen, 1985). TPB and its derivative, the technology acceptance model (TAM; Davis, 1989), have been used to investigate antecedents of participation and to predict intention to use sharing-based consumption. The review of our studies indicates that TPB (4 articles, 4.5%) has been used to investigate the influence of attitude, subjective and personal norms, and perceived behavioral control on the intention to participate in collaborative consumption; attitude has a strong positive impact (Cheah et al., 2020; Lindblom et al., 2018; Roos & Hahn, 2019) as well as subjective and personal norms, whereas no effect of perceived behavioral control on usage intention could be proven (Roos & Hahn, 2019).

Another theory in this cluster is the social cognitive theory (SCT, Bandura, 1989). According to SCT, there is a reciprocal determination among personal, environmental, and behavioral factors. Considering the interdependency of these factors, the environment of one’s consumption decision can often be decisive for the direction taken by one’s moral compass. In line with this assumption, Perren et al. (2019) use SCT to examine how the environment impacts behavior and personal factors and to demonstrate that greater duration of participation deteriorates moral identity centrality, which in turn can positively impact the likelihood of a recommendation.

4.5 Approaches without a Guiding Theory

Our review reveals that 34 articles (38.6%) do not draw on a specific theory. Eight articles without a guiding theory (9.1%) were conceptual (e.g., Etzioni, 2019; Gielens & Steenkamp, 2019; Pies et al., 2020), 11 articles (12.5%) involved quantitative methods (e.g., Gleim et al., 2019; Jaeger et al., 2019; Neunhoeffer & Teubner, 2018), 12 articles (13.6%) represented qualitative approaches (e.g., Barbosa & Fonseca, 2019; Gilal et al., 2019; Park & Armstrong, 2019b) and two adopted mixed-method approaches (2 articles, 2.3%; Lutz & Newlands, 2018; Pera et al., 2016).

5 Context

Table 3 and Table 4 summarize the research contexts, including business contexts, perspectives, industries, and countries investigated in the reviewed literature. The reported frequencies are based on 88 articles; as some articles include multiple studies and cover multiple industries and countries, the article count in the tables exceeds the total number of 88 articles.

5.1 Business Context and Perspective

Four different types of business contexts have been analyzed. Most of the studies in our sample concentrate on consumer-to-consumer sharing (77.3%), 15 articles display a general focus on the sharing economy (17.0%) and four studies investigate and compare business-to-consumer sharing (4.5%). We only had one publication in our sample that focuses on a specialized context of business-to-business contexts (1.1%). Almost half of the reviewed articles use a mixed perspective (48.9%) and do not focus on a single actor's perspective. Most of the studies (57 articles; 64.8%) investigate the consumer perspective, and 40 publications analyze the user view as a peer provider (45.5%). Twenty-three articles involved a platform-related perspective (26.1%). Twenty-one publications focused exclusively on the platform perspective (e.g., Habibi et al., 2017; Rangaswamy et al., 2020), although most of these articles were conceptual (11 articles; e.g., Eckhardt et al., 2019; Gielens & Steenkamp, 2019) or used mainly secondary data (8 articles, e.g., Laczko et al., 2019; Perren & Kozinets, 2018). We could only find one article that analyzes the platform perspective through empirical research with primary data in the form of interviews with thematic analysis with platform managers (Guillemot & Privat, 2019).

5.2 Industries

The type of exchanged goods or services affects the adoption, sharing process, and outcomes; therefore, we specifically reviewed the articles in the context of the industry. Half of the reviewed articles do not provide specific information and do not focus on a specific industry, product, or service (50.0%), making it difficult to interpret and compare the findings to other studies. Furthermore, our analysis suggests that the SE is mostly investigated in the accommodation industry (22.7%) and in the case of car sharing (13.6%; e.g., Wilhelms et al., 2017) and ride sharing (13.6%; e.g., Arteaga-Sánchez et al., 2020; Cheah et al., 2020). While the shared use of accommodation and cars does represent well-known practical examples, other industries account more for specialized sharing applications such as the fashion industry (4.5%; e.g., Pantano & Stylos, 2020; Park & Armstrong, 2019a) and household goods (8.0%; e.g., Hartl et al., 2016; Stofberg & Bridoux, 2019). Some SE research investigates industries that differ from classical product sharing, such as logistics and delivery (2.3%; e.g., Carbone et al., 2017; Mai et al., 2020), where goods are delivered by other users, and food sharing (2.3%; e.g., Berg et al., 2020; Harvey et al., 2020). We found one publication that investigated the sharing of intangible goods, Milanova and Maas (2017), which investigated the relevance of intangibility for sharing services and empirically examined consumers' motives, perceptions, and experiences in the context of peer-provided insurance sharing. Only a few studies involve multiple industries and draw comparisons based on shared products and services (e.g., Berg et al., 2020; Gupta et al., 2019; Oyedele & Simpson, 2018), making it difficult to generalize the findings.

Table 3: Context, Perspectives, and Industries investigated in SE Marketing Research

Context, perspectives, and industries	No. of articles	%	Exemplary studies
Business context			
Sharing economy in general	15	17.0	Apte and Davis (2019); Eckhardt et al. (2019); Yang et al. (2017)
Consumer-to-consumer	68	77.3	Albinsson et al. (2019); Benjaafar et al. (2019); Benoit et al. (2017)
Business-to-consumer	4	4.5	Fritze et al. (2020); Hazée et al. (2019);
Business-to-business	1	1.1	Laczko et al. (2019)
Perspective			
Consumer	57	64.8	Costello and Reczek (2020); Hartl et al. (2016); Mai et al. (2020)
Provider	40	45.5	Cheah et al. (2020); Ertz et al. (2017); Guyader (2018);
Platform	23	26.1	Guillemot and Privat (2019); Habibi et al. (2017); Kumar et al. (2018)
Industry			
Accommodation	20	22.7	Davidson et al. (2018); Ert and Fleischer (2020); Jaeger et al. (2019)
Car sharing	12	13.6	Gupta et al. (2019); Hofmann et al. (2017); Wilhelms et al. (2017)
Ride sharing	12	13.6	Arteaga-Sánchez et al. (2020); Hartl et al. (2020); Suri et al. (2019)
Bike sharing	2	2.3	Griffiths et al. (2019); Gupta et al. (2019)
Fashion and clothes	4	4.5	Gupta et al. (2019); Pantano and Stylos (2020); Park and Armstrong (2019b);
Household goods and services	7	8.0	Berg et al. (2020); Costello and Reczek (2020); Kim and Jin (2020)
Food	2	2.3	Berg et al. (2020); Harvey et al. (2020)
Logistics and delivery	2	2.3	Carbone et al. (2017); Mai et al. (2020)
Intangible goods	1	1.1	Milanova and Maas (2017)
Not specified	44	50.0	Albinsson et al. (2019); Philip et al. (2015); Yang et al. (2017)

Note: The reported frequencies are based on 88 included articles.

5.3 Countries

As illustrated in Table 4, most of the reviewed studies were conducted in the United States (29 articles, 33.0%) and Germany (13 articles; 14.8%). The dominant focus on the United States and Germany can be explained by two main reasons. First, most management science research is predominantly focused on mature markets in North America and Europe. Particularly, studies have indicated that research tends to overstate theories developed for the United States context that are poorly adapted to local circumstances and businesses in other countries (Tsui et al., 2007). Second, the sharing economy relies on information and communications technology and growing consumer awareness that both apply to developed countries rather than developing countries (Hamari et al., 2016).

Table 4: Countries investigated in SE Marketing Research

Country	No. of articles	%	Exemplary studies
North America	37	42.0	
United States	32	36.4	Akbar (2019); Jaeger et al. (2019); Perren et al. (2019)
Canada	5	5.7	Ertz et al. (2017); Ertz et al. (2018); Mercier-Roy and Mailhot (2019)
Europe	50	56.8	
Germany	14	15.9	Balderjahn et al. (2020); Neunhoeffer and Teubner (2018); Wilhelms et al. (2017)
United Kingdom	7	8.0	Harvey et al. (2020); Laczko et al. (2019); Pantano and Stylos (2020)
Spain	6	6.8	Arteaga-Sánchez et al. (2020); Akhmedova et al. (2020); Del Alonso-Almeida et al. (2020)
Austria	5	5.7	Hartl et al. (2016); Hofmann et al. (2017); Hartl et al. (2020)
Benelux (Netherlands and Belgium)	3	3.4	Aspara and Wittkowski (2019); Barbosa and Fonseca (2019); Lindblom et al. (2018)
Finland	3	3.4	Hazée et al. (2019); Stofberg and Bridoux (2019); Vith et al. (2019)
France	2	2.3	Guillemot and Privat (2019); Vith et al. (2019)
Italy	2	2.3	Mittendorf (2018); Vith et al. (2019)
Norway	2	2.3	Berg et al. (2020); Mittendorf (2018)

Sweden	2	2.3	Guyader (2018); Mittendorf (2018)
Other European countries[a]	4	4.5	Mittendorf (2018); Schivinski et al. (2020); Vith et al. (2019)
Asia	16	18.2	
China	5	5.7	Ma et al. (2020); Mai et al. (2020); Yang et al. (2017)
India	3	3.4	Albinsson et al. (2019); Davidson et al. (2018); Gupta et al. (2019)
Turkey	3	3.4	Gupta et al. (2019); Mittendorf (2018); Tunçel and Özkan Tektaş (2020)
South Korea	2	2.3	Gupta et al. (2019); Vith et al. (2019)
Other Asian countries[b]	3	3.4	Gupta et al. (2019)
Oceania	4	4.5	
Australia	2	2.3	Cheah et al. (2020); Vith et al. (2019)
New Zealand	2	2.3	Cheah et al. (2020); Philip et al. (2019)
Country not applicable	21	23.9	Benjaafar et al. (2019); Carbone et al. (2017); Lin et al. (2019)

Note: Some studies investigate more than one country. The reported frequencies are based on 88 included articles. [a] Includes Switzerland, Sweden, Denmark, Bulgaria, and Poland; [b] includes Pakistan, Philippines, and Russia.

Indeed, 16 studies in our sample (18.0%) were conducted in Asian countries. Five studies were performed in China, three studies in India and Turkey, and two in South Korea. Only three studies were conducted in a single Asian country (e.g., two articles were carried out in China; Ma et al., 2020; Yang et al., 2017; one article in Turkey; Tunçel & Özkan Tektaş, 2020), and all other studies were part of cross-national studies (e.g., Gupta et al., 2019; Mittendorf, 2018). In this matter, we observed interest in SE consumer behavior in Asian countries starting in 2017. Furthermore, four studies (4.6%) were conducted in Australia (Cheah et al., 2020; Vith et al., 2019) and in New Zealand (Cheah et al., 2020; Philip et al., 2019). In our sample, only one study included African respondents that were part of a cross-cultural study done by Gupta et al. (2019). Finally, it is noteworthy that 21 articles did not report any country, as these studies are based on netnographic data (e.g., Apte & Davis, 2019; Carbone et al., 2017;

Pera et al., 2016; Perren & Kozinets, 2018) or conceptual articles that did not include data for analysis; therefore, countries were not applicable (e.g., Benoit et al., 2017; Kumar et al., 2018).

The results of our analysis further reveal that most of the studies were conducted within a single country (55 studies). Only 12 articles collected data in cross-national studies (e.g., China and United States; Mai et al., 2020, United States and India; Albinsson et al., 2019, United States and Pakistan; Davidson et al., 2018) or include samples that involve multinational respondents (e.g., Gupta et al., 2019; Mittendorf, 2018; Vith et al., 2019). For example, Gupta et al. (2019) performed a multinational study including respondents from 11 countries all over the world to examine the influence of the dimensions of culture and product intimacy on the intention to rent and provide. However, the lack of cross-national research is problematic in light of the different personal beliefs and perceived value of users that can be rooted in cultural aspects of users. SE platforms need to understand what marketing design elements can be standardized across markets, consumers, and providers and what elements need to be adapted to achieve the desired critical mass of users and user behavior in local markets. Thus, single-country studies provide only partial insights because the findings cannot be directly compared and generalized.

6 Characteristics

Research in our sample investigates the adoption, process, and outcomes of sharing exchange processes. We cluster the variety of analyzed characteristics (variables) relating to the different perspective levels (user, exchange, platform, industry, and country). Table 5 provides an overview of the variables that have been used in the analyzed sample. We analyzed variables only in quantitative studies according to their role in each study. We excluded conceptual and qualitative studies that did not involve bi/multivariate relationships. Therefore, the reported frequencies are based on 52 quantitative articles. Furthermore, we distinguish between independent, mediating, moderating, and dependent variables.

Table 5: Characteristics investigated in SE Marketing Research

Characteristics	**No. of articles**	**%**
Independent variables		
User level		
Personal beliefs	18	34.6
Perceived value, benefits, and risks	15	28.8
Personal characteristics	11	21.2
Usage behavior	3	5.8
Exchange level		
Platform relationship characteristics	17	32.7
User relationship characteristics	14	26.9
Product/service characteristics	8	15.4
Platform level		
Organization & governance	5	9.6
Commission & pricing	3	5.8
Brand characteristics	1	1.9
Other variables	4	7.7
Mediating variables		
User level		
Personal beliefs	7	13.5
Perceived value, benefits, and risks	5	9.6
Usage behavior	4	7.7
Usage outcomes	4	7.7
Personal characteristics	3	5.8
Exchange level		
Platform relationship characteristics	10	19.2
User relationship characteristics	8	15.4
Platform level		
Brand characteristics	2	3.8
Moderating variables		
User level		
Personal beliefs	2	3.8
Perceived value, benefits, and risks	1	1.9
Exchange level		
Platform relationship characteristics	3	5.8
Product/service characteristics	2	3.8

Platform level		
Organization & governance	2	3.8
Commission & pricing	1	1.9
Dependent variables		
User level		
Usage behavior	34	65.4
Usage outcomes	13	25.0
Personal beliefs	1	1.9
Perceived value, benefits, and risks	1	1.9
Exchange level		
Platform relationship characteristics	4	7.7
User relationship characteristics	3	5.8

Note: The reported frequencies are based on 52 quantitative articles.

6.1 Independent Variables

Regarding the investigated independent variables (IVs), Table 5 illustrates the different groups of variables and their subgroups accordingly. Our review suggests that most studies include IVs on user and exchange levels.

User level variables capture various characteristics related to user personal characteristics (11 articles, 21.2%); personal beliefs, such as environmental concerns and moral foundations (18 articles, 34.6%); perceived values, benefits, and risks (15 articles, 28.8%); and usage behavior (3 articles, 5.8%). Perceived value and personal beliefs are two of the most common IVs used and are included in almost two-thirds of all the studies (a combined 63.6%). Personal beliefs refer to users' general attitudes and their cognitive and emotional predispositions. For example, research has demonstrated that collectivism, materialism, or openness to experience have a positive effect on users' intention to rent and provide (Albinsson et al., 2019; Lindblom et al., 2018; Tunçel & Özkan Tektaş, 2020), whereas uncertainty avoidance shows a negative effect (Gupta et al., 2019). Users' perceived value refers to the evaluation of benefits relative to the costs. To evaluate the perceived value, consumers, and providers simultaneously consider the different types of benefits (e.g., economic benefits in the form of cost savings for consumers or additional income for providers) and the effort related to the sharing exchange process (e.g., in the form of additional costs for providers or inconvenience costs for consumers). High perceived value positively affects the intention to use (e.g., Akbar, 2019; Roos & Hahn, 2019) and attitude toward platforms (e.g., Cheah et al., 2020; Hwang & Griffiths, 2017).

Variables on the exchange level concern the relationships between users, platforms, and products/services and include user-relationship characteristics, such as trust in the provider or consumer (14 articles, 26.9%), platform-relationship characteristics, such as familiarity with the platform and brand awareness (16 articles, 30.8%), and product/service characteristics, such as the type and quality of the accessed object (8 articles, 15.4%). Research has shown that product/service characteristics influence the likelihood of being shared, e.g., products with a high degree of intimacy are less likely to be provided and rented (Frechette et al., 2020) and that service quality positively influences the likelihood of choosing again. Interpersonal trust and interpersonal similarity are two examples of user-relationship characteristics (Hazée et al., 2019; Ma et al., 2020), whereas trust in platforms and self-congruence with platforms are examples of platform-relationship characteristics (Arteaga-Sánchez et al., 2020; Gleim et al., 2019).

Platform level IVs include various characteristics related to platform design: brand characteristics, such as functional or hedonic brand image (i.e., Schivinski et al., 2020), organization and governance, such as platform responsiveness and reliability as part of the CC-QUAL (quality of services provided through a collaborative consumption model) scale developed by Marimon et al. (2019) (i.e., Akhmedova et al., 2020) and commission and pricing mechanisms, such as commission rate (i.e., Benjaafar et al., 2019).

Less utilized IVs include industry-related variables, including the degree of substitutability and comparability with non-sharing forms (3 articles, 5.8%; e.g., Akbar, 2019; Berg et al., 2020) and internet capability (1 article; i.e., Möhlmann, 2015).

6.2 Mediating Variables

We found that 29 of the 88 assessed articles (50.0%) included mediators. Most of these mediators are related to user and exchange levels characteristics. Variables on the exchange level are used less frequently as mediators than user level variables. Exchange-related mediators included user-relationships (8 articles, 15.4%) and platform-relationship characteristics (10 articles, 19.2%). Typical relationship-related variables that mediate the effects of IVs on user behavior and outcomes are attitude toward peer users or platforms (e.g., Cheah et al., 2020; Hwang & Griffiths, 2017; Lindblom et al., 2018; Roos & Hahn, 2019) or trust (e.g., Aspara & Wittkowski, 2019; Lu et al., 2020; Mittendorf, 2018) that represent both factors to maintain and continue sharing behavior. In contrast, the most used mediators at the user level were personal beliefs (7 articles, 13.5%), perceived value (5 articles, 9.6%), and user outcomes (4 articles, 7.7%). User outcomes, for example, are satisfaction (e.g., Arteaga-Sánchez et al., 2020; Möhlmann, 2015) and well-being (e.g., Balderjahn et al., 2020; Seegebarth et al., 2016). Positive user outcomes positively affect the intention to continue sharing or to share again (e.g., Arteaga-Sánchez et al., 2020; Möhlmann, 2015) and the willingness to pay (i.e., Frechette et al., 2020). No article used country-related characteristics or industry-related characteristics as mediating variables, and only two articles facilitated platform-related characteristics as a mediating variable, namely, brand equity (Schivinski et al., 2020; Hazée et al., 2019).

6.3 Moderating Variables

Concerning moderating variables, our analysis indicates that only 10 articles (11.3%) take moderating effects into account. Moderators have been studied both from the user side, such as consumer characteristics, i.e., innovativeness; (Hwang & Griffiths, 2017) or independent self-view (Frechette et al., 2020), and from an exchange perspective, such as consumer attitude toward platform marketing (Cheah et al., 2020) or efforts during the exchange process (Perren et al., 2019) and the platform side, such as promotion design types (Mai et al., 2020) or commission mechanisms (Costello & Reczek, 2020). For example, Hwang and Griffiths (2017) show that consumer innovativeness has a significant positive moderating effect on the relationship between users' value perceptions (utilitarian, hedonic, and symbolic) and attitude and empathy toward collaborative consumption services. Balderjahn et al. (2020) show that perceived consumer empowerment (defined as a subjective state resulting from individuals' perceived sense of control; Corrigan et al., 1999) plays a significant role in the relationship between user personal consumption beliefs and well-being as one outcome. Costello and Reczek (2020) show that when sharing economy brands use provider-focused (vs. platform-focused) marketing communications, consumers perceive a purchase more as helping a single provider, which increases consumers' willingness to pay and their likelihood of downloading the brand's app.

6.4 Dependent Variables

Finally, our review of the investigated dependent variables (DVs) shows that most studies focus on user-related characteristics (43 articles; 82.7%), and only 13.5% (7 articles) of the reviewed quantitative articles focus on investigating DVs in terms of exchange. No article has analyzed DVs from the platform, country, or industry perspective.

Referring to user-related DVs, researchers focus in particular on (1) usage behavior (35 articles, 67.3) and (2) user outcomes (12 articles, 23.1%). Usage behavior DVs include variables directly related to the use of sharing, such as the intention to use (e.g., Costello & Reczek, 2020; Hazée et al., 2019; Stofberg & Bridoux, 2019), likelihood to share (e.g., Akbar, 2019; Aspara

& Wittkowski, 2019; Perren et al., 2019), intention to provide (e.g., Gupta et al., 2019; Hartl et al., 2020), usage levels (i.e., Albinsson et al., 2019; Benjaafar et al., 2019; Ertz et al., 2018) and intention to continue (Arteaga-Sánchez et al., 2020; Möhlmann, 2015) as well as indirectly related behavior such as likelihood to recommend (Perren et al., 2019) and failure forgiveness (i.e., Lu et al., 2020; Suri et al., 2019). Meanwhile, user outcome DVs describe, for example, psychological well-being (i.e., Balderjahn et al., 2020; Seegebarth et al., 2016), happiness (i.e., Li & Atkinson, 2020), satisfaction (Berg et al., 2020), social closeness (i.e., Frechette et al., 2020), psychological ownership (Li & Atkinson, 2020) and customer loyalty (i.e., Akhmedova et al., 2020; Yang et al., 2017). Due to the inherent objective of SE platforms of establishing and maintaining a critical mass of users, the quantity, and variety of usage behavior- and user outcome-related DVs are not surprising. Both are the prevailing DVs and have been studied consistently to understand why and how users participate in sharing-based consumption.

Frequent exchange-related DVs include user relationship-related and platform relationship-related variables. For both relationships, attitude and trust were the most studied variables, i.e., trust in peer users (Ert & Fleischer, 2020; Hofmann et al., 2017) or trust in the platform (Hofmann et al., 2017) and the attitude toward peer users (Roos & Hahn, 2017) or attitude toward the platforms (Hazée et al., 2019; Roos & Hahn, 2017). In general, research has shown that trust in and attitude toward the other party are two of the main antecedents of usage intention and behavior. Since sharing exchange can involve a triadic relationship between platforms, consumers, and providers, these variables play an even greater role and therefore have been studied primarily from an exchange perspective. Other unclassified DVs (7 articles, 6.0%) include market price and total consumer (social) welfare.

7 Methodology

To assess the literature in terms of methodology, we reviewed all 88 articles according to the research design (conceptual, quantitative, or qualitative), data collection approach (primary, secondary), and analytical method(s) used to investigate the relationships of interest. Table 6 summarizes our findings.

Table 6: Research Approaches and Methods used in SE Marketing Research

Research approach and method	No. of articles	%	Exemplary studies
Conceptual	14	15.9	Benoit et al. (2017); Eckhardt et al. (2019); Steenkamp (2020)
Quantitative	52	59.1	Aspara and Wittkowski (2019);
Qualitative	29	24.8	Buhalis et al. (2020); Guyader (2018); Scaraboto (2015)
Primary data	57	68.4	
Survey data	34	38.6	Roos and Hahn (2017); Caldwell et al. (2020); Davidson et al. (2018)
Experimental data	14	15.9	Costello and Reczek (2020); Hazée et al. (2019); Lu et al. (2020)
Interview data	12	13.6	Laczko et al. (2019); Milanova and Maas (2017); Wilhelms et al. (2017)
Secondary data	24	27.3	Pantano and Stylos (2020); Wruk et al. (2019); Zhang (2019)
Quantitative methods			
Structural equation modeling	21	23.9	Fritze et al. (2020); Gleim et al. (2019); Roos and Hahn (2019)
(Multivariate) analysis of (co)variance, t-test	17	19.3	Costello and Reczek (2020); Hazée et al. (2019); Mai et al. (2020)
Regression analysis[a]	15	17.0	Albinsson et al. (2019); Davidson et al. (2018); Jaeger et al. (2019)
Explorative factor/cluster analysis[b]	5	5.7	Akhmedova et al. (2020); Ertz et al. (2018); Neunhoeffer and Teubner (2018)
Numeric simulations[c]	2	2.3	Benjaafar et al. (2019); Jiang and Tian (2018)
Qualitative methods			
(Automated) content analysis	12	13.6	Etzioni (2019); Guyader (2018); Lutz and Newlands (2018)
Qualitative comparative analysis	3	3.4	Akhmedova et al. (2020); Perren and Kozinets (2018); Vith et al. (2019)
Grounded theory	3	3.4	Milanova and Maas (2017); Parker et al. (2019); Park and Armstrong (2019b)

Network analysis	2	2.3	Harvey et al. (2020); Wruk et al. (2019)
Thematic analysis	2	2.3	Guillemot and Privat (2019); Philip et al. (2015)
Other methods[c]	5	5.7	Apte and Davis (2019); Berg et al., 2020; Hartl et al. (2016)

Note: The number of articles amounts to more than 88 because 7 articles employ multiple methods (e.g., Ertz et al., 2017; Lutz et al., 2018; Yang et al., 2017); the reported frequencies are based on 88 included articles. [a] includes binary logistic regression (e.g., Stofberg & Bridoux, 2019), linear mixed model (e.g., Gupta et al., 2019), diff-in-diff models (e.g., Zervas et al., 2017), and canonical correlation analysis (e.g., Albinsson et al., 2019); [b] includes explorative factor analysis for scale development (e.g., Kim & Jin, 2020); [c] includes methods ranging from qualitative methods (i.e., case study, Apte & Davis, 2019; Laczko et al., 2019; Mercier-Roy & Mailhot, 2019) to quantitative methods (i.e., correspondence analysis, Hartl et al., 2016; descriptive analysis, Berg et al., 2020).

7.1 Research Approach

Our systematic review in terms of methodology, used in marketing and consumer behavior research about the SE, indicates that quantitative approaches lead the field, with 52 articles that include quantitative studies (59.1%) compared to 29 articles that include qualitative studies (33.0%) and 14 conceptual articles (15.9%). The overall number exceeds 88 articles due to several mixed-method articles.

Among the empirical articles that included quantitative and qualitative studies, 57 (64.8%) used primary data, and 24 used secondary data (19.5%). Two articles that we coded as quantitative articles do not include data because they incorporate numeric simulations (i.e., Benjaafar et al., 2019; Jiang & Tian, 2018). The type of data collection shows that survey studies focusing on exploring correlational relationships (34 articles; 38.6%) prevail over experimental studies that focus on exploring causal relationships (14 articles, 15.9%) and interview studies (12 articles, 9.0%) that focus on explorative qualitative methods. Secondary data include, among others, netnographic data from websites and platform apps (e.g., Wruk et al., 2019), transaction data (e.g., Ma et al., 2020) and market data (i.e., Zervas et al., 2017) that have been mainly used by qualitative studies (only four quantitative studies used secondary data, i.e., Aspara & Wittkowski, 2019; Burtch et al., 2018; Ma et al., 2020; Zervas et al., 2017).

7.2 Research Methods

Researchers use various analytical methods that are applied according to the data collected (see Table 6 and Section 7.1). As already stated, most of the publications are empirical, and quantitative studies within structural equation modeling are the most popular analytical method (21 articles, 23.9%). Fourteen of these studies used covariance-based structural equation modeling (15.9%), and seven articles incorporated variance-based structural equation modeling (8.0%). One of these seven studies used cross-lagged structural modeling based on a two-wave panel study to examine the effects of collaborative consumption on users' values, attitudes, and norms (Roos & Hahn, 2017). More than half of the studies that use structural equation modeling intend to explain why users differ in intention to use (12 articles). The second most frequently used group of methods applies to studies based on experimental data. This group included different forms of mean comparisons, such as multivariate analysis of (co)variance and t-tests (17 articles, 19.3%). Analogous to structural equation modeling, the focus of these methods is on exploring behavior and usage intention in different sharing settings. The third group of frequently used quantitative methods is regression analysis, where linear regression (OLS), binary logistic regression (e.g., Hartl et al., 2020; Stofberg & Bridoux, 2019), linear mixed models (e.g., Gupta et al., 2019), diff-in-diff models (e.g., Zervas et al., 2017) and canonical correlation analysis (e.g., Albinsson et al., 2019; Ertz et al., 2017) are included. Examples of more specialized methods include explorative analysis and numeric simulations (i.e., Benjaafar et al., 2019; Jiang & Tian, 2018). Five quantitative articles used explorative (1) factor analysis, e.g., for scale development (Kim & Jin, 2020) or (2) explorative cluster analysis, to uncover latent structures such as user groups (e.g., Ertz et al., 2018; Neunhoeffer & Teubner, 2018).

Compared to these quantitative methods, qualitative methods are used less frequently. The main qualitative method that has been used is the group of content analysis (12 articles, 13.6%), where we reviewed a set of different approaches, ranging from different manual approaches (e.g., Barbosa & Fonseca, 2019; Wilhelms et al., 2017; Yang et al., 2017) that mainly use interview data to more data-driven automatic approaches (e.g., Pantano & Stylos, 2020; Zhang, 2019) that use netnographic data from websites or platform apps. Furthermore, we designated qualitative comparative analysis (3 articles, 3.4%), grounded theory (3 articles, 3.4%), network analysis (2 articles, 2.3%), and thematic analysis (2 articles, 2.3%) as categories of qualitative methods.

Examples of articles that used other methods include methods ranging from qualitative (i.e., case study, Apte & Davis, 2019; Laczko et al., 2019; Mercier-Roy & Mailhot, 2019) to quantitative methods (i.e., correspondence analysis, Hartl et al., 2016; descriptive analysis, Berg et al., 2020).

In terms of research intent, we see that qualitative methods are often used to exploratively identify user motives to participate in the SE (e.g., Barbosa & Fonseca, 2019; Ertz et al., 2017; Liu et al., 2020; Park & Armstrong, 2019a), to analyze netnographic and case study data (e.g., Apte & Davis, 2019; Carbone et al., 2017; Laczko et al., 2019) and as a mixed-method approach to enhance quantitative studies (e.g., Akhmedova et al., 2020; Ertz et al., 2017; Lutz & Newlands, 2018; Yang et al., 2017). Quantitative studies focus especially on the adoption, usage, and outcomes of sharing-based consumption modes. Concerning the different methods, regression analysis is typically incorporated to examine the adoption intention (e.g., Albinsson et al., 2019; Hartl et al., 2020; Stofberg & Bridoux, 2019). Structural equation modeling is typically utilized for different hierarchical, multilevel purposes that can include moderation and mediation analysis, e.g., to analyze customer loyalty (i.e., Yang et al., 2017), well-being (i.e., Balderjahn et al., 2020; Seegebarth et al., 2016) and intention to use (e.g., Cheah et al., 2020; Hwang & Griffiths, 2017; Park & Armstrong, 2019a). Methods for multivariate analysis predominantly use experimental data and investigate several dependent variables, e.g., service failure forgiveness (i.e., Suri et al., 2019), trust (i.e., Hofmann et al., 2017) and adoption intention (e.g., Costello & Reczek, 2020; Hazée et al., 2019).

In terms of the methods used, it is important to point out that there is no single method that is fundamentally superior to others. Many studies use multiple methods (e.g., Fritze et al., 2020) and mixed-method approaches (e.g., explorative factor analysis (EFA) with fuzzy-set qualitative comparative analysis (fsQCA), Akhmedova et al., 2020; focus group interviews as preparation for survey and structural equation modeling, Yang et al., 2017) to consider different types of data sets from multiple sources in their articles to increase the generalizability of their results and reduce common-method bias (Podsakoff et al., 2003).

8 Future Research Agenda

Marketing and consumer behavior research has produced various studies on the sharing economy over the past years that have collectively improved our understanding of why and how users interact in sharing-based consumption modes. To structure and consolidate existing knowledge, we first provided a general overview of the SE marketing and consumer behavior research, followed by a detailed overview of theories used to explain phenomena in context; contexts in which these phenomena were studied; characteristics (i.e., variables) that were studied; and methods used to study variables, test their relationships, and draw conclusions about the relationships studied. Based on our review, we outline an agenda for future research to help advance the SE consumer behavior and marketing research. Based on our review structure, we again separate theory, context, characteristics, and methodology. It is noteworthy that the research directions presented are not exhaustive.

8.1 Recommended Research Agenda for the Theory

Although most of the reviewed articles draw on a specific theory, a broad range of approaches are used. Many articles rely on a single theory, and fewer articles use multi-theoretical perspectives that integrate different theories. However, a single theoretical approach is less likely to account for the complexity of the SE, which can feature multiple actors (platform, provider, and consumer) and multiple contexts (industries and countries). Therefore, future studies should adopt multi-theoretical perspectives and integrate different theories to account for the complexity.

Second, most theories analyze psychological processes that are user-related and exchange-related. Future studies should consider theories to examine the impact from provider and platform perspectives, e.g., how platform marketing can attract a critical mass of users. In this context, future research should consider not only possible benefits and risks but also characteristics derived from theories of self-perception. In addition, we call for theory usage and development that adequately addresses the role of platforms as central intermediaries in the exchange process.

Third, many theories applied to the SE are limited, as they suffer from explaining the complex dynamics that occur in sharing exchange. Most consumer-related theories originate in buy-and-own markets and are based on relationships between consumers and companies, but attempt to explain a multilateral phenomenon. Even if extended, they cannot present a comprehensive and dynamic picture of the SE. Other theories focus on social exchange and relationships between consumers and providers and neglect the relationships of both with the platforms. Further efforts are needed in selecting, customizing, and using theories that deal more with the relationship process among platforms, providers, and consumers. Therefore, and included with the first two points, multi-perspective approaches that leverage their complementarity could help explain additional variability in the investigation of the adoption, sharing process, and outcomes. For example, we did not find any empirical article that incorporated the theory of two-sided markets (Rochet & Tirole, 2003). The concept of two-sided markets was originally developed in economics and then gradually incorporated into management and marketing science research. Rooted in the literature on network externalities (Katz & Shapiro, 1985), the theory of two-sided markets defines platforms as intermediaries between two user groups that provide each other with network benefits. This theory could help to clarify the triadic relationships among platforms, providers, and users and support giving answers to important marketing and promotion questions to avoid a "chicken and egg" situation.

8.2 Recommended Research Agenda for the Context

Regarding the investigated contexts, many articles are set in a few specific applications, such as accommodation, car sharing, and ride sharing, or focus on the SE in general without having any industry context. Since 2019, studies have explored other industries, but these studies are less represented. The COVID-19 pandemic has heavily affected the overall SE and hurt established sharing platforms (e.g., Airbnb). However, it has also promoted the development of new applications, such as sharing of delivery rides services. Further, only one article is conducted in another business context than consumer-to-consumer or business-to-consumer. For example, business-to-business relationships differ from business-to-consumer or consumer-to-consumer relationships, as they are often oriented toward the long term. The SE can offer benefits in business-to-business markets when existing resources are collaboratively shared and costs are divided. Because even in the prominent sectors (e.g., accommodation and mobility industries), many aspects are still underexplored, and the research field continually develops (e.g., through the impact of COVID-19), we recommend two further research directions: first, generalize the findings by considering more examples from the current SE market (e.g., the increasing relevance of micromobility sharing for urban development); second, expand research to the context of other relationships (e.g., business-to-business).

Additionally, our review shows that most of the research in our sample was carried out in developed Western countries. As the SE is a global phenomenon that can generate various benefits for society, e.g., optimized usage of underutilized assets, as well as for users, e.g., a cost-efficient option of consumption without the burden of ownership, there is an additional need for research on emerging countries. Additionally, only a few studies (i.e., Albinsson et al., 2019; Davidson et al., 2018; Gupta et al., 2019; Mai et al., 2020; Mittendorf, 2018) account for cultural differences when analyzing consumer behavior. Therefore, future research in this field could study the adoption, sharing exchange process, and outcomes in varying market settings, including emerging and developing countries, to enhance and generalize prior findings and to study the moderating role of external factors, such as economic conditions, cultural particularities, and technological infrastructure.

Another research gap is as follows: when doing the review, we could only find one article that analyzes the platform perspective through empirical research with primary data. Most of the existing research from the platform perspective relies on secondary data analysis and is conceptual. To gain further insights into the SE from the platform standpoint, e.g., to understand the main challenges, key resources, and outcomes of such platforms, we suggest more empirical work not only to discover consumer behavior but also to gain insight into platform marketing management.

8.3 Recommended Research Agenda for the Characteristics

Regarding the investigated characteristics, we reveal that quantitative research has analyzed related phenomena from various perspectives, employing variables related to the user, exchange, platform, industry, and country. Compared to the quantity and quality of user-related and exchange-related variables, platform-related, industry-related, or country-related variables have so far received little. Few studies have explicitly considered the competitive context of the industry by comparing antecedents of behavior between sharing-based consumption and conventional consumption modes, i.e., car sharing vs. car ownership (for exceptions see Berg et al., 2020; Hofmann et al., 2017). SE platforms generally act in and often disrupt established markets with various competing conventional and innovative competitors. Therefore, it is important to understand the complex dynamics and the competition in the respective markets.

Finally, platform-related variables have played a minor role. For the success of SE businesses, it is crucial to create and maintain a critical mass of users and to generate revenues. To reach this goal, platforms have to fulfill several tasks, e.g., formulating value propositions to users (Guyader, 2018; Wruk et al., 2019), generating demand for the supply side (Kumar et al., 2018; Perren & Kozinets, 2018), and providing governance systems (Benoit et al., 2017; Hartl et al., 2016) while creating trust and reducing the perceived risks. Such platform-related characteristics could be considered factors that potentially influence consumers' adoption.

Regarding user-related and exchange-related characteristics, our review shows that various characteristics have been used. However, sharing-based consumption can also raise issues related to security and privacy risks. Research has shown that privacy concerns and loss of control are both causes of potential doubt, stress, and a decline in well-being that hinder adoption and use (Cloarec, 2020; Martin & Murphy, 2017). Privacy issues are also gaining importance in the sharing economy literature (Lutz et al., 2018; Teubner & Flath, 2019). Future research should shed light on peer users' privacy calculus (Awad & Krishnan, 2006) or the trade-off between privacy risks (e.g., the potential cost associated with the release of personal information to the platform and peer users) and benefits.

In general, we have identified many studies that address acceptance and usage behavior and analyze related characteristics. Many of these studies, which typically draw on theories of technology acceptance and usage behavior, are conducted in the context of the accommodation, car sharing, and ride sharing industry. Considering our ever-changing economic and social environment, increasingly being affected by external effects (e.g., the COVID-19 pandemic, Russo-Ukrainian War), and the fact that in the sharing economy, people engage in social exchanges, investigating the future adoption and use of sharing-based consumption in times of crisis could be a point of interest. Therefore, the identification and examination of pandemic-related antecedents (e.g., hygiene criteria) or crisis-related antecedents (e.g., inflation) could be an area of research.

Finally, regarding investigated characteristics, most of the variables in the quantitative articles are self-reported and declarative. Self-report surveys are the preferred method of data collection for most researchers because they are inexpensive, relatively simple, flexible, and allow researchers to study behaviors that might otherwise be unobservable (Kormos & Gifford, 2014; Tarrant & Cordell, 1997). While some studies suggest self-reports as adequate predictors of actual behavior (Corral-Verdugo, 1997; Corral-Verdugo & Figueredo, 1999), other research raises concerns for some reasons, including systematic response bias, method variance, and mono-method bias, and the reliability and validity of questionnaire scales (Brener et al., 2003; Fisher, 1993; Nenycz-Thiel et al., 2013). Therefore, we suggest more research concerning characteristics of real-world behavior of sharing-based consumption.

8.4 Recommended Research Agenda for the Methodology

Finally, and with respect to the methods used in our sample, our findings attest to the research domain’s novelty. We found conceptual and qualitative studies in addition to the dominant quantitative studies that rely on primary data from experiments and surveys. The data types inform the choice of method, in that survey data tend to be analyzed by using structural equation modeling, experimental data by conventional multivariate tests, and regression analysis is relevant for both types of data.

While experimental data can offer high levels of internal validity, secondary data on real behavior (e.g., market and transaction data) offer a higher level of external validity and are key to testing the generalizability of findings in real-world settings. However, SE research using secondary data on real behavior is scarce, and many studies rely on single-source data to test their propositions, especially in the context of surveys (22 out of 34 studies that use surveys as a data source have a single-source design). This raises the issue of common-method bias that can harm the validity of estimated parameters and reduce the ability to detect moderating effects. Therefore, the use of multiple data sources for different model constructs is an effective way to avoid such biases (Podsakoff et al., 2003). Access to transaction data of SE platforms tends to be more restricted (i.e., for reasons of user data protection), and the use of secondary data has been limited. However, consumer analytics based on big data, which is defined as hidden insight into consumer behavior through advantageous interpretation, is increasingly becoming important for consumer behavior and marketing research, as well as for firms (Erevelles et al., 2016; Hofacker et al., 2016). Therefore, we suggest that future research should use mixed-data approaches to leverage the unique strength of both primary and secondary data. By combining more reliable real-world and usage data (from firms, test fields, or laboratories) with primary data from experiments and surveys, studies can reduce the risk of common-method bias and simultaneously enhance internal and external validity.

Moreover, marketing and consumer behavior research would benefit from more longitudinal studies and analysis. So far, little is known about the effects of sharing-based consumption on individuals and their perceptions. Based on our sample, only one article analyzed the effects of shared consumption on future attitudes, subjective norms, and personal norms (Roos & Hahn, 2017). Individual values can change based on individual learning, testing, and use experiences, as experience with behavior can potentially lead to a change in values if they do not match the behavior performed (Thøgersen & Ölander, 2002). Therefore, we suggest more empirical research incorporating longitudinal data to examine effects on user perceptions and evaluation of sharing-based consumption over time and to deepen our understanding of user experience on the user evaluation of sharing-based consumption.

Finally, another underutilized big data source is posts, comments, or other user artifacts on SE platforms. Advanced text mining and automated text analytics can identify latent structures using sentiment analysis and can generate influential marketing and consumer behavior insights (Humphreys & Wang, 2018). Although most marketing problems are interdisciplinary, marketing and consumer behavior research is often fragmented (i.e., qualitative vs. quantitative research). Therefore, automated text analytics has the potential to unify the field with a common set of tools and approaches (Berger et al., 2020). In fact, two of our reviewed articles used automatic content analysis and semantic topic modeling (Pantano & Stylos, 2020; Zhang, 2019) to analyze customer reviews and Twitter tweets. Further research could use text data in the form of reviews to measure user-related variables (such as attitude or trust toward peer users) to correlate these measured variables with, for example, usage frequency while avoiding some biases of traditional surveys, such as social desirability.

9 Summary of the Chapter

The sharing economy represents a steadily growing part of our global economy, in which people can consume without having to buy and own. This chapter has revieved 88 articles using the theory-context-characteristics-methodology (TCCM) framework protocol (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018) to paint a comprehensive and precise picture of the field and to develop a future research agenda. By using this framework, we answer the following questions: what theories have been used to explain consumer behaviors in the sharing economy (e.g., the adoption, sharing process, and outcomes)?; in what contexts (e.g., industries, countries) has research been investigated?; what characteristics from the user, exchange, and platform perspective have been studied?; and what methods have been utilized in marketing and consumer behavior research? The review reveals an existing focus on user- and exchange-related theories. While there is much research on accommodation sharing and ride sharing (due to the best-known examples of Airbnb and Uber), we identified contribution gaps for more recent and controversial applications of the sharing economy (e.g., micromobility sharing). Regarding investigated characteristics, we see little empirical research from a non-user perspective and research would contribute from studying not only intentions but also real use and possible outcomes. This, in turn, opens up chances from a methodological perspective. For instance, literature would contribute from investigating real-world behavioral data and from using longitudinal data to increase the internal validity of further insights. The upcoming parts of the thesis focus on closed-campus micromobility as an example of shared mobility innovations that are provided by organizations to their users. We suggest that this type of investigation is important for some reason: 1) it investigates a highly debated application of sharing-based consumption in the mobility sector; 2) enhances the literature about adoption behavior in terms of shared mobility innovations to overcome the dark sides of the sharing economy; 3) focuses not only on the analysis of survey data but moreover on real behavioral data.

Thus, in the following chapters, we contribute to the literature and close some of the just highlighted gaps. First, we investigate the antecedents of consumers' initial adoption to use shared micromobility in closed-campus environments and whether the intention to use actually leads to real use. Second, we use different theories to account for the complexity of the adoption process. Third, we do investigations in the domain of micromobility sharing for urban development. Fourth, we use mixed-data approaches to leverage the unique strength of both primary and secondary data by combining survey-based declarative data and actual real behavioral data of sharing-based consumption. In this way, we increase internal and external validity while reducing the risk of common-method bias.

Introduction

Chapter 1.
A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Chapter 3.
Satisfaction and Continuance Intention with Closed-campus Micromobility

Chapter 4.
Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Conclusion

Chapter 2.

Antecedents of Adoption and Usage of Closed-campus Micromobility

Abstract

Shared micromobility is an innovative way of urban transportation that provides low-emission short-distance travel options and can reduce reliance on using private vehicles, especially in urban areas (Abduljabbar et al., 2021; McQueen et al., 2021). However, it is also a controversial topic, because of randomly parked vehicles on sidewalks, risky riding behavior, and vandalism (Gössling, 2020; Useche et al., 2022). Closed-campus micromobility solutions are deployed in limited areas such as university or office campuses, are only available to the campus community (Shaheen et al., 2020), and are seen as a promising way to overcome the dark sides of existing shared micromobility services. This article analyzes initial user acceptance and real adoption behavior of users of a closed-campus micromobility service. Based on the well-established unified theory of acceptance and use of technology (Venkatesh et al., 2012), we consider how constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015) and from trust-rsik theories (Martin & Murphy, 2017; Pavlou, 2003), influence initial behavioral intention and real use behavior. To test the proposed antecedents of adoption and real use, we use structural equation modeling with both survey and real behavioral data from users (N=199) of DHBW Drive, a field laboratory for micromobility at Baden-Wuerttemberg Cooperative State University in Stuttgart, Germany. The results of structural equation modeling reveal that perceived performance expectancy, effort expectancy, task enablement, and hedonic

and utilitarian value are significant antecedents of behavioral intention, which in turn positively affects the real use of our study participants.

Figure 10: Chapter 2 – Objectives, Methodology, and Publications

OBJECTIVES	• Investigate antecedents of initial adoption (first use) of closed-campus micromobility • Extend UTAUT2 (Venkatesh et al., 2012) with new antecedents adopted to the context: consumer perceived value, task enablement, privacy concerns, and technology trust • Study the influence on real use behavior by incorporating mixed-data approach (survey and behavioral data; Blut et al., 2021)
METHODOLOGY	• Structural equation modeling • 199 users of service DHBW Drive – Survey data: after start of the service DHBW Drive (26/11/20-19/12/20) – Behavioral data: after survey completion until end of the service DHBW Drive (28/02/22)
PUBLICATIONS	Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2022). Lime, Bird or Campus Drive? Where Institutions can be ahead of Markets - An Empirical Study about Consumers' Intention to use Closed-campus Micromobility. 2022 Academy of Marketing Science Annual Conference, Monterey Bay (CA), US, May 25-27. Targeted Journal: Journal of the Association for Information Systems

1 Introduction

‘Sustainable cities and communities’ is one goal within the 17 sustainable development goals of the United Nations (United Nations, 2022), and air pollution, noise, and congestion have led to a technology-driven paradigm shift in the transportation sector in cities all over the world. Innovative mobility services are facilitated by technological advancements in electrification, automation, and on-demand shared travel and consequently change consumers’ mobility behavior. In this new mobility environment, shared micromobility services are experiencing exponential growth and adoption in urban centers (Shaheen et al., 2020). Shared micromobility is an innovative way of urban transportation that provides short-distance travel options and enables a sustainable transition away from individual motorized transport (Eccarius & Lu, 2020; Gössling, 2020). The most popular form of shared micromobility is e-scooter sharing (e.g., Spin, Lime), which provides users with a fun, convenient, and flexible way to fulfill their short-distance trips. Since 2015, stakeholders have invested more than $5.7 billion in micromobility start-ups and, consequently, shared e-scooters, bicycles, and other forms of micromobility vehicles have conquered cities around the world (McKinsey & Company, 2019). But although micromobility and especially e-scooters are fast-growing global consumer phenomena, they are also controversial and highly debated topics. While on the one hand, they offer many advantages for urban traffic, in contrast, they also cause controversies. Clutters of randomly parked vehicles on sidewalks, risky riding behavior, and vandalism are major issues associated with shared micromobility services (Abduljabbar et al., 2021; Gössling, 2020).

Shared micromobility services can be station-based, free-floating, or hybrid (Shaheen et al. 2020) and research about shared micromobility services has shown that station-based systems are most efficient in terms of sustainability. This applies particularly in areas with higher employment or higher number of nearby attractions and where micromobility is most commonly and carefully used by definable user groups (e.g., near universities and in central business districts; Bai & Jiao, 2020; Reck et al., 2021). Thus, an innovative concept that combines the aspects of station-based and definable user groups is particularly promising. It is therefore not surprising that the well-known shared micromobility platform Spin in June 2022 announced that they will invest up to $2 million in a partnership with Michigan State University and the University of Utah to optimize transportation outcomes in campus environments (Spin, 2022). Therefore and for our research, we refer to the term "closed-campus micromobility" to describe a transportation solution that provides access to shared use of micromobility vehicles (such as e-scooters) only available for members of a certain organization (e.g., employees of a company, members of an office campus, students/employees of a university).

As shared micromobility can make an important contribution toward more sustainable future mobility, understanding how to establish users' acceptance is an important task. However, we still know little about why users adopt or reject such shared micromobility as closed-campus solutions that can transform their mobility behavior. Past literature on shared micromobility is insufficient because a) it does rarely account for closed-campus systems, and b) is limited in investigating behavioral intention to use shared micromobility services. To our best knowledge, we only found two publications that investigate the adoption of shared micromobility in professional and closed-campus environments. First, Fernández-Heredia et al. (2016) studied the introduction of an internal bike system at a university campus in Madrid, Spain, and, second, Sun and Duan (2021) investigated a case of campus bike sharing at Dalian Maritime University, China. However, both studies do not rely on established models of technology and service acceptance research and therefore lack important additional insights into psychological factors of adoption (e.g., performance and effort expectancy, social influence).

Consequently, to our best knowledge, this research is the first to analyze the antecedents of consumers' behavioral intention to use closed-campus micromobility from a technology adoption perspective. Furthermore, using DHBW Drive, a field laboratory for micromobility at the Cooperative State University of Baden-Wuerttemberg (DHBW) in Stuttgart, Germany, as a case study, we analyze not only behavioral intention but also real use behavior by considering behavioral data such as total travel time or total travel distance of our study participants. Therefore, we theoretically contribute to this research gap in the following ways. First, we enhance the unified theory of acceptance and use of technology (UTAUT2; Venkatesh et al. 2012), to establish a conceptual model that explains the adoption factors of closed-campus micromobility use by incorporating consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), trust theory (McKnight & Chervany, 2001; Pavlou, 2003) and privacy calculus theory (Martin & Murphy, 2017; Meyer-Waarden & Cloarec, 2022). Second, we operationalize and test the model using an empirical survey and real behavioral usage data, which is rare in the technology acceptance literature and represents an additional contribution (Blut et al., 2021). From a managerial perspective, the results help inform mobility platform operators and possible customers (e.g., universities, office campuses, and businesses), policymakers, and transportation planners seeking to improve micromobility adoption and management.

Our article is organized as follows. First, we provide a theoretical background about closed-campus micromobility, the literature about micromobility adoption, and the conceptual framework that explains the antecedents of behavioral intention to use and real use of closed-campus micromobility. Consequently, we formulate our hypotheses, followed by a description of the methodology and data. We then present and discuss the results. Finally, we highlight the implications for theory and practice, address the limitations of the research, and outline future research directions.

2 Theoretical Background

In the following section, we first explain the term closed-campus micromobility, provide a theoretical background, and then elaborate on the conceptual model that explains the antecedents of behavioral intention to use and real use of closed-campus micromobility.

2.1 Closed-campus Micromobility

The term “closed-campus” was first introduced by Shaheen and Chan (2016) in the context of bike sharing systems that “are increasingly being deployed at university and office campuses and are only available to the particular campus community they serve” (Shaheen & Chan, 2016, p. 580). For our further research, we use the term “closed-campus micromobility” (CCMM) that describes a transportation solution that provides access to shared use of micromobility vehicles only available for members of a certain organization.

Regardless of whether the service is freely accessible or only available in a closed environment, the operation model of shared micromobility services can be station-based, dockless, or hybrid (Shaheen et al., 2020). In a station-based system, users access and return the device at fixed-located stations. In a dockless, or free-floating, system, users access and return the micromobility device at any location within a predefined geographic region. A hybrid system combines both of the previously discussed operating models. Previous studies about bike sharing systems show that stations in areas with higher employment or with a higher number of nearby attractions are more efficient because more arrivals and departures occur (Faghih-Imani et al., 2017). This is in line with analyses of e-scooter usage data that e-scooters are most commonly and carefully used by definable user groups near universities and in central business districts (Bai & Jiao, 2020; Caspi et al., 2020; Reck et al., 2021).

As stated in the introduction section, CCMM services combine aspects of station-based and limited user groups and represent a new and innovative solution that has also been recognized by the established micromobility providers in the market (i.e., Spin, 2022). Similar to Spin, since August 2021 the market competitor Lime is partnering with the city of Boulder and the University of Colorado to deploy 200 e-scooters and to provide non-vehicular travel options for area employees, students, and residents (City of Boulder, 2022). However, it is not only a market opportunity for established providers, but also for new specialized providers. One example is the innovative mobility start-up evhcle in Munich, Germany. It is an all-in-one mobility service provider that enables e-mobility and micromobility solutions for hotels, serviced apartments, residential neighborhoods, and municipalities (evhcle, 2022).

2.2 Literature Review

Although the subject of shared micromobility has recently attracted researchers' attention, the literature that systematically and empirically investigates initial adoption intention and behavior is still sparse and emerging. Table 7 presents empirical research that systematically and empirically investigated the initial adoption intention and use behavior of shared micromobility innovations. In terms of investigated context, the literature indicates that most of the studies have studied public solutions, and only two articles investigated closed-campus solutions. Fernández-Heredia et al. (2016) studied the introduction of an internal bike system at a university campus in Madrid, Spain, and found that the perception of convenience (e.g., efficiency, flexibility), pro-cycling attitude (e.g., ecological, cheap, healthy), physical determinants (e.g., fitness level of user) and external restrictions (e.g., climate) help to explain intention to use the mobility service. In addition, Sun and Duan (2021) investigated a case of campus bike sharing at Dalian Maritime University, China, and conclude that service quality positively and safety risk negatively impact the intention to use. However, both studies do not draw on an established theory based on a technology adoption model, and, thus, lack important additional theoretical insights into psychological factors (e.g., performance and effort expectancy, social influence). Furthermore, and concerning campus context, two studies do not explicitly investigate closed-campus solutions but focus their investigation on university samples. Chevalier et al. (2019) analyze the acceptance behavior of public bike sharing systems depending on built environment factors (e.g., urban typology) of five university campuses across Shanghai, China. Similarly, Eccarius and Lu (2020) investigate what factors influence university students' intention to use an e-moped sharing service, and, conclude that attitude, behavioral control, and subjective norm are significant drivers, which are all in turn significantly influenced by compatibility to mobility needs and awareness knowledge of students.

Moreover, most studies investigate bike sharing and few studies focus on other micromobility modes (e.g., e-scooter, e-bikes). For example, Li et al. (2020) find that the service quality of bike sharing has a positive effect on attitude toward the service and behavioral intention to use. Moreover, they demonstrate that subjective norms and behavioral control are also influential factors of behavioral intention. Few studies investigate public e-scooter sharing. For example, Kopplin et al. (2021) reveal factors affecting shared e-scooter usage from a consumer's perspective. They show that performance expectancy, hedonic motivation, and environmental concerns are positive drivers, whereas perceived safety impedes the intention to use. The strong focus on bike sharing is also evident when considering the context studied from a country perspective. The majority of the studies were conducted in Asian countries. In contrast to western countries, where car-centric culture is common, bicycles have been the main mode of transportation in China since the last decade of the 20th century (Chevalier et al., 2019; Ye, 2022). Only three studies investigate Western countries (i.e., Germany; Kopplin et al., 2021, United States; Blazanin et al., 2022, Spain; Fernández-Heredia et al., 2016). However, understanding and promoting the motivations for switching from motorized individual transport (in the form of a private car) is essential for realizing the full potential of shared micromobility.

For this reason, more research should be conducted on the adoption of shared micromobility in car-centric Western cultures.

Concerning used theories and investigated characteristics, many studies draw on the theory of planned behavior (TPB, Ajzen, 1991). Other studies draw on the technology acceptance model (TAM, Davis, 1989), and one study uses the unified theory of acceptance and use of technology (UTAUT, Venkatesh et al., 2003). Moreover, two studies combine technology acceptance theories. For instance, Gao et al. (2019) investigate perceived usefulness and ease of use (based on TAM) as well as facilitating conditions and social influence (based on UTAUT) as antecedents of public bike sharing in China, and conclude that perceived usefulness and facilitating conditions are significant drivers but perceived ease of use and social influence are not. Similarly, Khajehshahkoohi et al. (2022) use variables from TPB and from TAM to show that perceived behavioral control, attitude, and subjective norms (based on TPB) have a positive effect on behavioral intention to use public bike sharing, and that ease of use and usefulness (based on TAM) increase attitude. Based on the underlying adoption theory, the studies enhance their models with additional variables. These variables range from personal beliefs (e.g., environmental concerns or technology interests of the respondents) psychological perceptions of the service (e.g., compatibility, safety risk), and personal or built environment factors (e.g., vehicle ownership, population density). Concerning dependent variables: Although, three articles investigate similar but other variables (i.e., acceptance level; Chevalier et al., 2019, willingness to switch; Wang et al., 2021; willingness to pay; Song et al., 2021), in adoption behavior models the variable of ”behavioral intention to use” is the common dependent variable to be predicted. However, strong behavioral intention does not ultimately lead to real use behavior, which should be the main interest in adoption behavior research. Four studies investigated use behavior as a dependent variable. However, these studies measured real use behavior survey-based and self-reported by asking for the frequency of the actual use

(Blazanin et al., 2022; Kopplin et al., 2021; Li et al., 2020; Xin et al., 2019). This type of self-reported measurement of use frequency has disadvantages in terms of reliability and validity since it is retrospective and does not capture future usage resulting after the survey.

In summary, the literature review shows that understanding “how and why users adopt shared micromobility services” is an important issue. Although the use of shared micromobility is enjoying great interest in the market and public discussion, and despite the growing number of studies in this area, we detect influential gaps to contribute. First, most of the studies were done in the context of public micromobility sharing. The two articles, which investigated closed-campus solutions (Fernández-Heredia et al., 2016; Sun & Duan, 2021), did not draw on an established theory, such as the technology adoption models, and, thus, lack essential additional theoretical insights into psychological factors (e.g., performance and effort expectancy, social influence). Furthermore, the research drawing on TAM, TPB and UTAUT, misses important perceptions, motivations, and barriers specific to the context of closed-campus micromobility and overall shared micromobility. Since these technology acceptance models are often criticized as unable to be adapted (Benbasat & Barki, 2007) and in line with recommendations of a recent meta-analysis about technology adoption (Blut et al., 2021), the literature recommends including rarely or not yet investigated cognitive, social and affective antecedents. For example, shared micromobility is promoted for its manifold added consumer value, which can range from utilitarian benefits (e.g., more convenient, quicker, and safer than walking), economic benefits (e.g., saving time and money), environmental benefits (e.g., more sustainable, environmentally friendly than a private vehicle) to hedonic benefits (e.g., fun/relaxing). However, a comprehensive investigation of consumer perceived value dimensions in terms of shared micromobility is missing. Moreover, other rarely investigated antecedents, such as technology trust and privacy concerns, would help to understand barriers in the adoption process of shared micromobility solutions in closed-campus environments.

Second, there is a strong focus on shared micromobility research in Asian countries and on the application of bike sharing. Less research was done in Western countries (Blazanin et al., 2022; Kopplin et al., 2021) and on the application of e-scooter sharing (Kopplin et al., 2021; Rejali et al., 2021). However, to realize the full potential of shared micromobility and to promote the switch from motorized individual transport to more sustainable shared use of mobility, it is essential to understand adoption factors in countries where the car is used as the prevailing means of transportation (BCG, 2020; Lukasiewicz et al., 2022). Moreover, more research about the highly debated topic of e-scooter sharing can help to further develop the existing business models and to enhance the understanding of the adoption factor for shared micromobility services in general.

Table 7: Overview of Research about Shared Micromobility Adoption Intention

Study	Context	Theory	IV	DV	Methodology
Fernández-Heredia et al. (2016)	Campus bike sharing	-	Pro-bike attitude, Convenience, External restrictions, Physical determinants	Behavioral intention	3,048 university members in Madrid, Spain; Mixed logit model
Chen and Lu (2016)	Public bike sharing	TAM	Attitude, Perceived usefulness, Perceived ease of use	Behavioral intention	262 users and 262 non-users in Taipei City, Taiwan; Multi-group CB-SEM (AMOS)
Wu et al. (2019)	Public bike sharing	TAM	Perceived usefulness, Perceived ease of use, Facilitating conditions, Enjoyment	Behavioral intention	1,020 respondents in Tianjin, China; Hierarchical regression analysis
Xin et al. (2019)	Public bike sharing	TPB	Attitude, Subjective norm, Perceived behavioral control, Habit	Behavioral intention, Self-reported use	211 users in China; PLS-SEM (SmartPLS)

Gao et al. (2019)	Public bike sharing	TAM, UTAUT	Perceived usefulness, Perceived ease of use, Social influence, Facilitating conditions, Perceived risk	Behavioral intention	298 respondents in China (panel survey); CB-SEM (AMOS)
Chevalier et al. (2019)	Public bike sharing	-	-	Level of acceptance	1,131 university students in China; Ordinal linear regression (R software)
Chen (2019)	Public bike sharing	TPB	Technology trust, Environmental value, Subjective norm	Behavioral intention	255 users and 255 non-users in Taipei City, Taiwan; CB-SEM (AMOS)
Li et al. (2020)	Public e-bike sharing	TPB	Attitude, Subjective norms, Perceived behavioral control, Service quality	Behavioral intention, Self-reported use	503 respondents in China; PLS-SEM (SmartPLS)
Zhu et al. (2020)	Public bike sharing	TPB	Attitude, Subjective norms, Perceived behavioral control, Environmental concern	Behavioral intention	998 users in China; PLS-SEM (SmartPLS)
Eccarius and Lu (2020)	Public e-moped sharing	TPB	Environmental values, Perceived compatibility, Awareness Knowledge, Attitude, Perceived behavioral control, Subjective norm	Behavioral intention	425 university students in Southern Taiwan; CB-SEM (STATA)
Huang et al. (2020)	Public dockless bike sharing	-	Green value, Pleasure, Personal Norms, Awareness of consequences, Ascription of responsibility	Behavioral intention	308 respondents in Chengdu, China; PLS-SEM (SmartPLS)
Rejali et al. (2021)	Public e-scooter sharing	TAM	Attitude, Perceived usefulness, Perceived ease of use, Hedonic motivation, Environmental awareness, Subjective norms	Behavioral intention	1,078 respondents in Iran; PLS-SEM (SmartPLS)

Sun and Duan (2021)	Campus bike sharing	-	Social value, Service quality, Safety risk, Convenience, Cost	Behavioral intention	317 university students in Dalian, China; CB-SEM
Kopplin et al. (2021)	Public e-scooter sharing	UTAUT2	Performance expectancy, Effort expectancy, Social influence, Hedonic motivation, Environmental concerns, Perceived safety	Behavioral intention, Self-reported use	749 respondents in Germany; Multi-group PLS-SEM (SmartPLS)
Wang et al. (2021)	Public bike sharing	-	Perceived risk, Relative advantage, System attributes: Complexity, Compatibility, Trialability, Observability	Willingness to switch	209 respondents in China; mediated regression analysis (PROCESS)
Song et al. (2021)	Public bike sharing	TAM	Perceived usefulness, Perceived ease of use, Perceived value, Perceived entertainment, Perceived cost, Perceived risk, Technology trust, Environmental value, Paying Consciousness	Willingness to pay	502 respondents in China; CB-SEM (AMOS)
Blazanin et al. (2022)	Public bike and e-scooter sharing	-	Safety concerns, Time consciousness, Green lifestyle propensity	Behavioral intention, Self-reported use	1,107 in Austin, United States; Generalized Heterogeneous Data Model (GHDM)
Khajehshahkoohi et al. (2022)	Public bike sharing	TAM, TPB	Perceived Ease of Use, Perceived Usefulness, Attitude, Interest in Technology, Perceived Behavioral Control, Subjective Norm	Behavioral intention	846 respondents in Grogan; Iran; CB-SEM (AMOS)

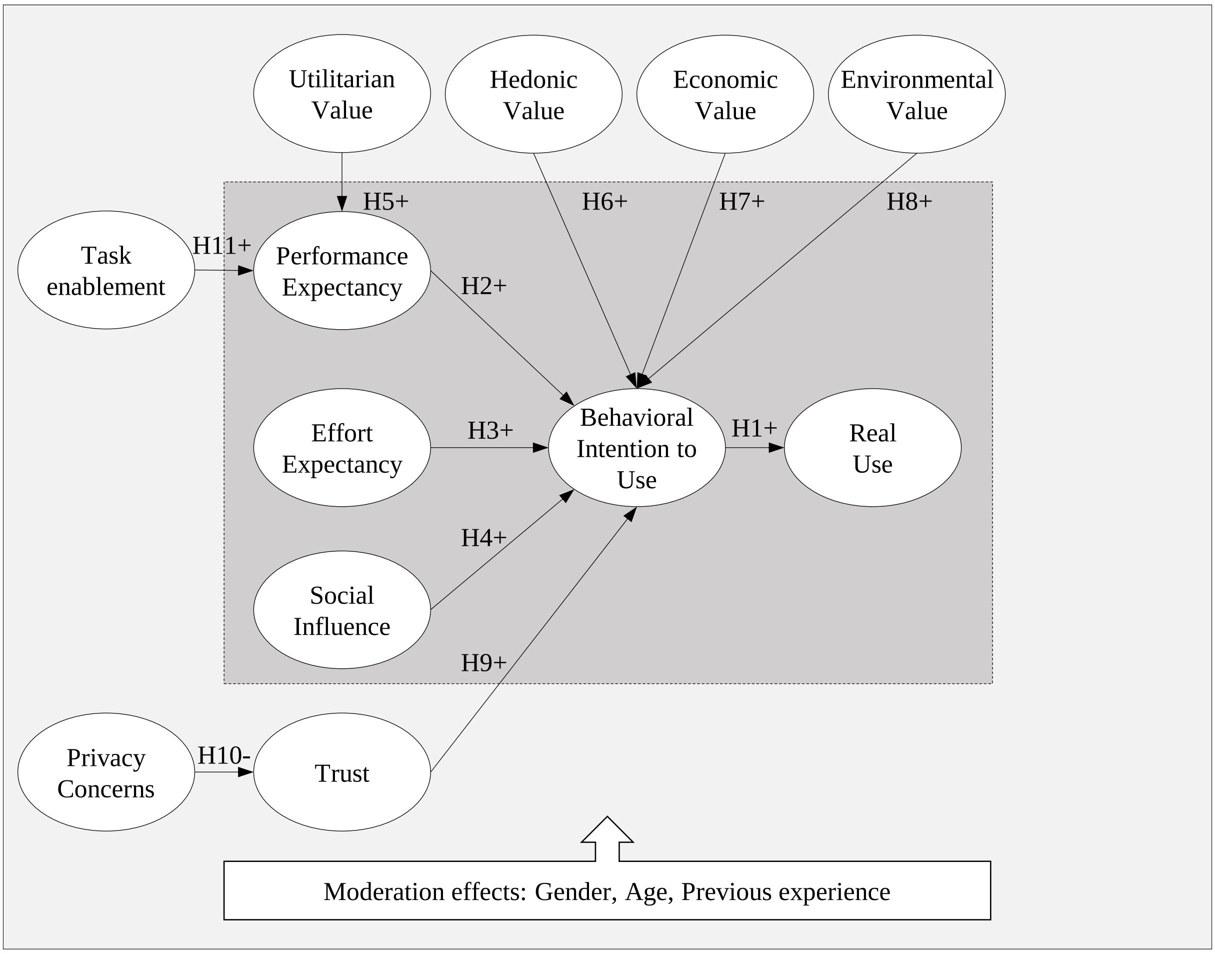
Note: IV = Independent variables; DV = Dependent variables

2.3 Conceptual Model and Hypotheses

Research needs to understand the context-specific factors that influence potential users' decisions to use shared micromobility services in closed-campus settings, to consider them in development, implementation, and marketing. Technology acceptance models and theories, all originating in sociology, psychology, and communication science, have been applied in a wide variety of fields to understand and predict use behavior (Blut et al., 2021). As shown in the literature review, the most commonly used and prevalent models are the theory of planned behavior (TPB; Ajzen, 1991), the technology acceptance model (TAM; Davis, 1989), and the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al., 2003). For our research, we choose the more recent UTAUT2 (Venkatesh et al., 2012) since it is considered the most effective integrated model for analyzing new technology adoption and behavioral intention of usage (Blut et al., 2021; Venkatesh et al., 2012).

We contribute to the UTAUT2 and technology acceptance literature by adding new theories and associated constructs. First, we incorporate consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), with consumer perceived value being defined as "the overall assessment of the utility of a product based on perceptions on what is received and what is given" (Zeithaml, 1988, p. 14). Indeed, shared micromobility having specific features (e.g., users do not own the vehicle but use it only temporarily), the perceived value of such a solution can be manifold. Therefore, a comprehensive investigation of consumer perceived value specific to the context of closed-campus micromobility will help to understand what dimensions matter most for potential users. Second, as we are investigating closed-campus micromobility which applies to organizational and professional environments, we add employee enablement theory (Adler & Borys, 1996; Permana et al., 2015) with perceived task enablement, which refers to the provision of work necessities and environment and has its roots in employee enablement theory. By providing mobility options for on-campus and off-campus travel, organizations can enable their members to better accomplish their daily tasks. Investigating if and how perceived task enablement can lead to higher acceptance and usage, can provide valuable information for organizations. Furthermore, we integrate additional cognitive variables of mobility innovation adoption, coming from trust-risk theories, such as technology trust (Pavlou, 2003) and privacy concerns (Martin & Murphy, 2017). Our conceptual model and the hypotheses are formalized in Figure 11 and will be described in the following.

Figure 11: Conceptual Model about the Adoption of Closed-campus Micromobility



2.3.1 UTAUT2, Behavioral Intention and Real Use Behavior

In the UTAUT2, behavioral intention to use refers to the motivational factors that influence a given behavior (Venkatesh et al., 2003). The stronger the intention to perform the behavior is, the more likely it is that the actual use behavior or real use will be performed

(Venkatesh et al., 2012). Research shows a strong positive correlation between behavioral intention to use and real use behavior of a technology (Dabholkar & Bagozzi, 2002; Lucas & Spitler, 1999). Applied to the mobility context, we hypothesize that the behavioral intention to use CCMM should impact positively the real use behavior. Thus:

Hypothesis 1. Intention to use positively influences real use of CCMM by users.

2.3.2 UTAUT2, Performance and Effort Expectancy

Further, the UTAUT2 uses several core variables, including performance expectancy and effort expectancy. Performance expectancy refers to "users' perceptions that using a new technology will improve their performance" (Venkatesh et al., 2003, p. 447) and effort expectancy refers to the "degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). Performance and effort expectancy are both important aspects when accepting new technologies, and both are positively related to behavioral intentions to use new technologies (Venkatesh et al., 2012). As shared micromobility systems are operated by the users on mobile devices, such solutions can be deemed as a technology application of mobile services. Consequently, previous research in the context of shared micromobility services has proven a positive impact of performance expectancy on behavioral intention (e.g., for the adoption of e-scooter sharing; Kopplin et al., 2021, or bike sharing; Gao et al., 2019) and of effort expectancy on behavioral intention (e.g., for bike sharing adoption, Chen & Lu, 2016). Thus, we formulate the following hypothesis:

Hypothesis 2. Performance expectancy positively influences the intention to use CCMM.

Hypothesis 3. Effort expectancy positively influences the intention to use CCMM.

2.3.3 UTAUT, Social influence

Social cognitive theory shows that the adoption of new technologies is influenced by social learning and recognition (Bandura, 1989). Social influence (SI) is the "degree to which individuals perceive that important others believe they should use the new system" (Venkatesh et al., 2003, p. 451). Thus, an important motivation for individuals to adopt a new technology is the desire to gain social status as people generally want to be accepted by groups and therefore follow group norms, defined as the most common pattern of overt behavior for members of a given social system, which in turn impacts the intention to use a new technology (Cooper et al., 2001). Although the use of micromobility is a solo activity (because e-scooters or bicycles cannot be used by more than one individual at one time), individuals may be persuaded to engage in usage because their social environment does likewise. Moreover, individuals may want to impress others by making their mobility behavior more innovative or innovative through the shared micromobility service. Accordingly, different studies on the acceptance of shared mobility have confirmed the importance of social influence on behavioral intention to use. For example, studies have demonstrated this relationship in the context of bike sharing (e.g., Khajehshahkoohi et al., 2022) and e-scooter sharing (e.g., Kopplin et al., 2021). Therefore, we formulate our hypothesis:

Hypothesis 4. Social influence positively influences the intention to use CCMM.

2.3.4 Consumer Perceived Value

Consumer perceived value is defined as "the overall assessment of the utility of a product based on perceptions on what is received and what is given" (Holbrook, 1994; Zeithaml, 1988, p. 14). Our review of micromobility studies regarding consumer perceived value shows that micromobility provides several substantial benefits (Abduljabbar et al., 2021; Sanders et al., 2020; Smith & Schwieterman, 2018) that range from utilitarian benefits (e.g., more convenient, quicker, and safer than walking), economic benefits (e.g., saving time and money), environmental benefits (e.g., more sustainable, environmentally friendly than a private vehicle) to hedonic benefits (e.g., fun/relaxing).

First, utilitarian value refers to consumers' perception of whether their needs are met in functional terms or whether adoption behavior contributes to utilitarian performance (Babin et al., 1994). Micromobility services provide utilitarian value because in specific circumstances (e.g., urban traffic situations) they are faster, easier, and more convenient to use than other transportation alternatives (e.g., car, public transit, or walking). For example, Ye (2022) shows that utilitarian value in terms of fast mobility solutions has a positive impact on the intention to use bike sharing services. Moreover, Lyu and Zhang (2021) investigate utilitarian value in terms of traffic performance and detect a positive impact on the perceived usefulness of bike sharing. Because utilitarian values are strongly related to consumer's evaluation of usefulness and performance expectancies (Chaudhuri & Holbrook, 2001), we assume that perceived utilitarian value directly increases performance expectancy and indirectly the propensity to use micromobility to maximize one's profit and hypothesize the following:

Hypothesis 5. Perceived utilitarian value positively influences the performance expectancy of CCMM.

Second, hedonic value refers to the users' overall judgments of experiential and emotional benefits of using a product or service (Babin et al., 1994) that are more subjective and personal than other factors and result more from consumer aesthetics, exploration, fun, and entertainment than from task completion (Meyer-Waarden & Cloarec, 2022). Many studies have investigated the positive impact of enjoyment and hedonic value on behavioral intentions, and show that micromobility is valued for being fun and relaxing. For example, Chen (2016) documented perceived enjoyment as one of the key constructs influencing continuance intention with bike sharing services. Similarly, Kopplin et al. (2021) detect a positive association between perceived enjoyment and intention to adopt e-scooters. Thus, we hypothesize the following:

Hypothesis 6. Perceived hedonic value positively influences the intention to use CCMM.

Third, economic value refers to the consumers' perception when comparing the costs and benefits of using a product or service. When the benefits of use outweigh the cost of money, the economic value is positive (Venkatesh et al., 2012). If the use of CCMM shows a better cost-benefit ratio compared to previous or alternative transportation options, economic value can have a positive effect on the intention to use such a service. Research has proven that economic value plays a significant role in the shared use of products and services (Barnes & Mattsson, 2017), e.g., Arteaga-Sánchez et al. (2020) show the impact of economic benefits on continuance intention to use ride sharing services. Likewise, Sun and Duan (2021) demonstrate the effect of access costs to decrease the intention to use campus bike sharing. Based on a road survey among e-scooter users in Paris, Christoforou et al. (2021) reveal that time and money saving were the main motivations to use e-scooters instead of other transportation modes. Therefore, we hypothesize the following:

Hypothesis 7. Perceived economic value positively influences the intention to use CCMM.

Fourth, environmental value refers to the consumers' perception of whether using a service or product improves the environmental performance in specific areas of their lives, and also includes an assessment of the sustainability and environmental friendliness of the used product (Chen, 2016). As micromobility solutions are considered to be an important component to reduce reliance on private vehicles and improve public health, studies have investigated that green perception was an important factor in explaining behavioral intentions to use micromobility (Chen, 2019; Flores & Jansson, 2021; Huang et al., 2020). For instance, Chen

(2019) investigate that perceived environmental value for users of bike sharing has a significant positive influence on using intention of bike sharing. Similar results have been proven by Huang et al. (2020) who investigates the effect on perceived green value in the context of dockless bike sharing. Therefore, we hypothesize:

Hypothesis 8. Perceived environmental value positively influences the intention to use CCMM.

2.3.5 Technology Trust

Consumer decisions involve beliefs about trust, since consequences cannot be anticipated with certainty (McKnight et al., 2011). Therefore, cognitive factors, based on prevention-oriented goals (Avnet & Higgins, 2006), such as technology trust (McKnight et al., 2011), are relevant in recent technology acceptance models of mobility (Meyer-Waarden & Cloarec, 2022) as it can be especially helpful in overcoming the uncertainty and facilitating the acceptance of new technologies and services (Hernández-Ortega, 2011; Pavlou, 2003). The research employs two different types of trust in technology constructs (Lankton et al., 2015). The first refers to human-like trust, such as benevolence, integrity, and ability, when the technology is perceived as human (e.g., online recommendation agents and robots; Benbasat & Wang, 2005). The second refers to system-like trust, such as helpfulness, reliability, and functionality, when the technology is system-like and refers to a particular technology (e.g., McKnight et al., 2011). We incorporate the system-like technology trust perspective which reflects the understanding of how technology operates and is defined as the extent to which a person expects that the new technology is reliable, credible, and dependable (McKnight & Chervany, 2001). In the context of mobility innovations, especially the direct impact of trust on behavioral intention to use has been shown. For example, Meyer-Waarden and Cloarec (2022) demonstrate that trust in the technology of an autonomous car is a strong predictor of usage intention. Chen (2019) and Song et al. (2021) provide evidence of the relationship between technology trust and the intention to use and pay for public bike sharing. Similarly, Javadinasr et al. (2022) prove the positive effect of technology trust for the intention to re-use e-scooter sharing. Accordingly, we assume that the more users trust the closed-campus micromobility technology, the more positive will be the impact on their usage intentions. Thus:

Hypothesis 9. Technology trust positively influences the intention to use CCMM.

2.3.6 Privacy Concerns

Because consequences cannot be predicted with certainty, consumer decisions about technology adoption involve beliefs about potential risks (Slovic, 1987). Technology risks, such as privacy concerns, hacking, data stealing, addiction, physical injuries due to potential loss of control, as well as ethical concerns are perceived as the main fears of data-based technologies. Therefore, cognitive prevention-oriented factors (Avnet & Higgins, 2006), such as privacy concerns, have high relevance in recent technology acceptance models about service robots and artificial intelligence-enhanced products (Meyer-Waarden et al., 2021; Meyer-Waarden & Cloarec, 2022; Wirtz et al., 2018). Privacy concerns refer to the extent to which users are concerned about influencing and controlling the collection, storage, and sharing of their personal information (Malhotra et al., 2004; Martin & Murphy, 2017). Due to the amount of personal data that is progressively collected, stored, transmitted, and published in online services, privacy concerns are an area of research with increasing attention (Awad & Krishnan, 2006; Hong & Thong, 2013; Martin & Murphy, 2017), particularly for sharing services (Lutz et al., 2018). Registration for shared micromobility services requires the provision of personal information, such as name, date of birth, and place of residence. In addition, shared micromobility can track the location and routes of a user and provide information such as routes, attractions, and traffic conditions (Li et al., 2019). While individuals, as citizens and consumers, can make individual choices to protect their privacy, it is more difficult to take such actions in the workplace or within an organization where individuals are usually subject to practices and environments dictated by the organization or their superiors (Ball et al., 2012). If users perceive privacy risks associated with the collection and use of their data through a closed-campus micromobility service, feelings of stress may arise and consequently, technology trust in the service may decrease due to privacy-related anxiety (Hong & Thong, 2013). We thus hypothesize:

Hypothesis 10. Privacy concerns negatively influence users' technology trust in CCMM.

2.3.7 Task Enablement

The term task enablement has its roots in the employee enablement theory (Adler & Borys, 1996). Perceived enablement is defined as "the extent to which employees feel they are provided with what they need to do their jobs well and are provided with an environment in which they feel comfortable to perform to the best they can be" (Permana et al., 2015, p. 580). An enabling work environment is understood as one that provides the tools and processes to improve employee performance (Colenbaugh & Reigel, 2010). Following this definition, closed-campus micromobility services can be understood as an infrastructural tool provided by the organization to its members to enable them to perform better in daily life. For instance, Sanders et al. (2020) analyze e-scooter use within a professional population and show that e-scooters are seen as a more convenient and faster way for travel purposes within the university campus, particularly in the heat and compared to walking (Sanders et al., 2020). By providing a more convenient, and fast mobility option for on-campus and off-campus travel purposes (e.g., transfer between buildings due to meetings, lunch break, customer visits), shared micromobility services can both enable users to save time and effort dedicated to existing work, and feasibly enable workflows that might not have been possible in the past due to time and other constraints (Buehler et al., 2021; Sanders et al., 2020). This in turn should positively impact users' perceptions of performance expectancy of the service. Thus, we hypothesize the following:

Hypothesis 11. Task enablement positively influences the performance expectancy of CCMM.

2.3.8 Moderating Variables

Gender, age, and experience have been shown to moderate relationships in the technology adoption process (Venkatesh et al., 2012). For example, age moderates the relationship between effort expectancy and intention to use so that the effects are stronger for younger people (Venkatesh et al., 2003). Moreover, the relationship between effort expectancy and behavioral intention to use is found to be moderated by gender, with men reporting that effort expectancy is more important than females (Gefen & Straub, 1997). Furthermore, the moderation effect of experience on the relationship between effort expectancy on behavioral intention has been investigated, as increasing experience should minor the effect of effort expectancy on behavioral intention (Davis et al., 1992). In terms of social influence, research postulates that gender, age, and experience have a moderating effect on the relationship between social influence and behavioral intention, especially for women and younger individuals (Binde & Fuksa, 2013; Venkatesh et al., 2012). In terms of trust, some studies show that women tend to be more anxious about the adoption of new technologies than men (Faqih, 2016; Mikkelsen et al., 2002). Finally, former studies indicate that the perceptions of consumer perceived value can be influenced by age, gender, and experience (Binde & Fuksa, 2013; Molinillo et al., 2021; Venkatesh et al., 2012). For example, Binde and Fuksa (2013) demonstrate a moderating effect of age, gender, and experience on the relationships of hedonic and economic value on behavioral intention. Thus, we include gender, age, and experience as moderating variables in our conceptual model.

3 Methodology

In the following section, we first describe the research field laboratory DHBW Drive and then our sample, the measurement instruments, and outline the used methodology.

3.1 DHBW Drive – a Field Laboratory for Closed-campus Micromobility

DHBW Drive was a field laboratory for shared closed-campus micromobility at Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany, and represents the first successful micromobility sharing system in a closed-campus environment of a German university. With the service, members of the university (approx. 7,000 students and 400 staff) could move between 5 university sites in downtown Stuttgart. In total, a fleet of 70 e-scooters was free-of-charge available and could be rented and parked at defined stations via an app, customized for the field laboratory and available for Android and iOS smartphones. At the stations, the e-scooters were charged using an in-house developed charging concept. Over the duration of the operation, from October 2020 to February 2022, more than 2,200 persons were registered (with a share of 95% of students), more than 12,200 bookings were made, and a total of more than 38,600 km were traveled.

3.2 Sample Characteristics

Our sample is based on an online survey, conducted with registered users of DHBW Drive. The survey was distributed via email-list to, at this time, 1,087 registered users. During the data collection period from 26/11/2020 to 19/12/2020, we received a data set of fully completed 487 responses. The survey included one reversed item as well as one attention check (i.e., "I am not paying attention at all in this survey. Please tick 'Fully disagree'") to detect inattentive respondents and increase statistical power (Abbey & Meloy, 2017). After the deletion of the inattentive respondents, 458 responses remained for statistical analysis. The survey included the "prefer not to answer" (PNA) response option (Albaum et al., 2010; Sischka et al., 2022). As for our statistical analysis, only complete responses without missing values could be used, 199 responses were valid for statistical analysis. 95% of our respondents were students and 5% were employees of the university (see Table 8). The gender distribution of our respondents was 24.6% females and 75.4% males. Furthermore, the average (median) age was 21.78 (20) years. Our sample is thus not representative of the German population. However, the age and function distributions are representative of a German university. Furthermore, it can be argued that samples from younger populations facilitate comparability and represent a promising segment for the use of new mobility forms, as younger generations tend to be more attracted to new technologies, products, and services (Attie & Meyer-Waarden, 2023; Barbosa et al., 2019; Mcmillan & Morrison, 2006; Meyer-Waarden & Cloarec, 2022).

Table 8: Sample Description

Variable	**Value**	**Total**	**Relative [%]**
Age	19 and younger	66	33.2
	20 – 29	122	61.3
	30 – 39	3	1.5
	40 – 49	5	2.5
	50 – 59	3	1.5
Gender	Male	150	75.4
	Female	49	24.6
Function	Student	189	95.0
	Staff / Lecturer	10	5.0
Prior experience with shared micromobility	Known but not used	54	27.1
	Sporadically used	87	43.7
	Frequently used	58	29.1
Total		199	100

3.3 Measurement Instruments

All measurement scales were adapted from previous studies (Table 9). Responses were collected based on a seven-point Likert scale (1 = fully disagree, 7 = fully agree).

To measure behavioral intention of use (e.g., "BI1: I intend to use the service DHBW Drive in the future.; BI2: I will try to use the service DHBW Drive in my daily life.; BI3: I plan to make regular use of the service DHBW Drive."), effort expectancy (e.g., "EE1: The use of the service DHBW Drive is effortless for me. EE2: My interaction with the service DHBW Drive is clear and understandable.; EE3: I find the service DHBW Drive easy to use.; EE4: Learning how to use the Service DHBW Drive is easy for me."), as well as performance expectancy (e.g., "PE1: I find the service DHBW Drive useful in my daily life.; PE2: Using the service DHBW Drive increases my chances of achieving important things.; PE3: Using the service DHBW Drive helps me get things done more quickly.; PE4: Using the service DHBW Drive increases my productivity."), and social influence (e.g., "SI1: People who are important to me think that I should use the service DHBW Drive when making mobility decisions.; SI2: People who influence my behavior think that I should use the service DHBW Drive.; SI3: People whose opinions I value prefer that I use the service DHBW Drive."), we used the scales from Venkatesh et al. (2012).

To measure utilitarian value (e.g., "UTT1: The service DHBW Drive makes it easier for me to reach my destinations.; UTT2: The service DHBW Drive makes my journeys convenient and more practical.; UTT3: The service DHBW Drive makes my journeys quicker."), we adapted a scale from Meyer-Waarden (2013). To measure hedonic value (e.g., "HED1: Using the service DHBW Drive is fun.; HED2: Using the service DHBW Drive is enjoyable.; HED3: Using the service DHBW Drive is very entertaining."), we used the scale from Venkatesh et al. (2012). Economic value (e.g., "ECO1: I can save money by using the service DHBW Drive.; ECO2: Using the service DHBW Drive can improve my economic situation.; ECO3: Using the service DHBW Drive benefits me financially.") and environmental value (e.g., "ENV1: The use of the service DHBW Drive is environmentally friendly.; ENV2: I feel that I am contributing to a sustainable environment by using the service DHBW Drive. ENV3: The service DHBW Drive is an example of a green service.") were both measured with a scale taken from Barnes and Mattsson (2017).

Technology trust (e.g., "TR1: The service DHBW Drive is reliable.; TR2: The service DHBW Drive is trustworthy.; TR3: Overall, I can trust the service DHBW Drive.") was measured with a scale from Sheinin et al. (2011). To measure privacy concerns (e.g., "PC1: It bothers me when the service DHBW Drive asks for personal data.; PC2: I am concerned that the service DHBW Drive collects too much personal data.; PC3: I am concerned that personal data I give to the service DHBW Drive for one reason may be used for another reason.; PC4: I am concerned that the service DHBW Drive may collect my personal data and share it with others.; PC5: I am concerned if I do not have control over the personal data I provide to the service DHBW Drive.; PC6: It concerns me if I have no control over how my personal data is collected, used and shared by the service DHBW Drive.") we used the scale from Hong and Thong (2013)

For the measurement of task enablement (e.g., "ENA1: The service DHBW Drive enables me to better manage my work/studies, tasks and appointments (lectures, etc.).; ENA2: The service DHBW Drive helps me get from faster A to B.; ENA3: The service DHBW Drive helps me to better balance my work/studies with my leisure time.; ENA4: The service DHBW Drive enables me to work better with my colleagues/fellow students."), we developed a four-item scale based on Permana et al. (2015).

To measure the dependent variable real use, we incorporated behavioral data provided by the backend of the service DHBW Drive. We used the total count of bookings [#] as a single item. As time period, we counted all bookings made per user after individual survey response time until 28/02/2022. To ensure data protection and anonymity, survey data were linked with behavioral use data through a two-step process. The full scales and items can be seen in Table 9.

To reduce the likelihood of common-method bias (CMB), we used two approaches. First and based on the CMB marker technique of Richardson et al. (2009), we separated the dependent variables (i.e., the behavioral intention of use) spatially from the independent variables by inserting a theoretically irrelevant marker variable between the two areas (see also Lindell & Whitney, 2001; Malhotra et al., 2006; Venkatesh et al., 2012). Second, CMB exists when either a) a general factor emerges from the data or b) a single factor explains most of the variance (Podsakoff et al., 2003). To test for CMB, we used Harman's single-factor test. The single factor explained 31% of the total variance. Since the total variance extracted by one single factor does not exceed the recommended threshold of 50%, CMB was not an issue (Harman, 1976).

3.4 Assessment of the Measurement Instruments

We conducted a confirmatory factor analysis to test the reliability and validity of the measurement instruments by using the software R 3.6.1 and the lavaan package (Rosseel, 2012). To assess convergent validity, we checked for indicator loadings below the recommended threshold value of .708 (Hair et al., 2019, p. 8). Indicators with loadings below the threshold value were removed from the initially specified measurement instrument (see Table 9). A second aspect of convergent validity refers to the average variance extracted (AVE), which clearly exceeded the minimum threshold of .5 for all constructs (see Table 9; Hair et al., 2019, p. 9). To assess reliability, we checked all latent constructs for Cronbach's α. All latent constructs showed values above the recommended threshold of .7 (see Table 9; Hair et al., 2019, p. 8).

Table 9: Scales, Reliability (α), Convergent validity (AVE), and Loadings

Constructs, sources, and items	α	AVE	Load.
Economic value (Barnes & Mattsson, 2017)	.91	.79	
ECO1: I can save money by using the service DHBW Drive.			.81
ECO2: Using the service DHBW Drive can improve my economic situation.			.88
ECO3: Using the service DHBW Drive benefits me financially.			.96
Hedonic value (Venkatesh et al., 2012)	.85	.66	
HED1: Using the service DHBW Drive is fun.			.85
HED2: Using the service DHBW Drive is enjoyable.			.93
HED3: Using the service DHBW Drive is very entertaining.			.71
Utilitarian value (Meyer-Waarden, 2013)	.87	.70	
UTT1: The service DHBW Drive makes it easier for me to reach my destinations.			.82
UTT2: The service DHBW Drive makes my journeys convenient and more practical.			.89
UTT3: The service DHBW Drive makes my journeys quicker.			.78
Environmental value (Barnes & Mattsson, 2017)	.91	.78	
ENV1: The use of the service DHBW Drive is environmentally friendly.			.81
ENV2: I feel that I am contributing to a sustainable environment by using the service DHBW Drive			.92
ENV3: The service DHBW Drive is an example of a green service.			.90
Privacy concerns (Hong & Thong, 2013)	.81	.61	
PC1: It bothers me when the service DHBW Drive asks me for personal data.			-
PC2: I am concerned the service DHBW Drive is collecting too much personal data.			.71
PC3: I am concerned that personal data I give to the service DHBW Drive for one reason may be used for another reason.			.85
PC4: I am concerned that the service DHBW Drive may collect my personal data and share it with others.			-
PC5: I am concerned if I do not have control over the personal data I provide to the service DHBW Drive.			.76
PC6: It concerns me if I have no control over how my personal data is collected, used and shared by the service DHBW Drive.			-
Technology trust (Sheinin et al., 2011)	.75	.65	
TR1: The service DHBW Drive is reliable.			.82

TR2: The service DHBW Drive is trustworthy.			-
TR3: Overall, I can trust the service DHBW Drive.			.78
Task enablement (Permana et al., 2015)	.90	.75	
ENA1: The service DHBW Drive enables me to better manage my work/studies, tasks and appointments (lectures, etc.).			.86
ENA2: The service DHBW Drive enables me to get faster from A to B.			-
ENA3: The service DHBW Drive enables me to better balance my work/studies with my leisure time.			.88
ENA4: The service DHBW Drive enables me to work better with my colleagues/fellow students.			.86
Social influence (Venkatesh et al., 2012)	.83	.71	
SI1: People who are important to me think that I should use the service DHBW Drive when making mobility decisions.			.90
SI2: People who influence my behavior think that I should use the service DHBW Drive.			-
SI3: People whose opinion that I value prefer that I use the service DHBW Drive.			.78
Effort expectancy (Venkatesh et al., 2012)	.91	.72	
EE1: The use of the service DHBW Drive is effortless for me.			.84
EE2: My interaction with the service DHBW Drive is clear and understandable.			.91
EE3: I find the service DHBW Drive easy to use.			.87
EE4: Learning how to use the service DHBW Drive is easy for me.			.77
Performance expectancy (Venkatesh et al., 2012)	.88	.66	
PE1: I find the service DHBW Drive useful in my daily life.			.81
PE2: Using the service DHBW Drive increases my chances of achieving important things.			.80
PE3: Using the service DHBW Drive helps me get things done more quickly.			.82
PE4: Using the service DHBW Drive increases my productivity.			.82
Behavioral intention of use (Venkatesh et al., 2012)	.86	.72	
BI1: I intend to use the service DHBW Drive in the future.			.79
BI2: I will try to use the service DHBW Drive in my daily life.			.81
BI3: I plan to make regular use of the service DHBW Drive.			.92

To evaluate discriminant validity, we used the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). All HTMT ratios showed good scores (see Table 10). Only the relation between task enablement (ENA) and performance expectancy (PE) exceeded the conservative threshold of .85 but still met the upper limit of .90 for constructs that are conceptually very similar (Henseler et al., 2015, p. 127).

Table 10: Discriminant Validity (HTMT Ratios)

Construct	**M**	**SD**	**ECO**	**HED**	**UTT**	**ENV**	**PC**	**TR**	**ENA**	**SI**	**EE**	**PE**	**BI**
ECO	4.57	1.85											
HED	6.41	.68	.37										
UTT	6.00	1.02	.46	.38									
ENV	4.93	1.36	.57	.30	.42								
PC	2.90	1.25	.20	.13	.07	.27							
TR	5.77	.89	.39	.36	.36	.53	.24						
ENA	4.65	1.61	.67	.29	.70	.57	.12	.38					
SI	4.22	1.59	.53	.20	.51	.60	.17	.43	.65				
EE	6.26	.74	.15	.44	.23	.23	.20	.51	.21	.18			
PE	5.24	1.24	.60	.38	.71	.53	.18	.43	.88	.62	.19		
BI	5.87	1.06	.57	.57	.67	.45	.22	.46	.71	.43	.39	.71	

Note: ECO = Economic Value; HED = Hedonic Value; UTT = Utilitarian Value; ENV = Environmental Value; PC = Privacy Concerns; TR = Technology Trust; ENA = Task Enablement; SI = Social Influence; EE = Effort Expectancy; PE = Performance Expectancy; BI = Behavioral Intention of Use

Overall, the measurement models achieved acceptable fit according to the usual fit indices: the chi-square/df ($\chi 2$/df) was less than 2.5; the comparative fit index (CFI) and Tucker-Lewis Index were greater than .90; and the root mean square error of approximation (RMSEA) was not greater than .08 (Anderson & Gerbing, 1988). The fit indices of the measurement models are summarized in Table 11.

Table 11: Measurement Model Fit Indices

	χ^2	df	RMSEA	CFI	TLI
Measurement model	679	462	.049	.953	.943

4 Results

To test the hypotheses, we conducted structural equation modeling (SEM), mediation analysis, and moderation analysis using the software R 3.6.1 and the lavaan package (Rosseel, 2012). Table 12 shows the fit indices for the structural equation model, which again achieved a good fit (RMSEA < .08, CFI > .90, and TLI > .90). The results of the SEM, the estimated direct path coefficients, and p values that indicate the direct effect of one variable on another variable are presented in Table 13.

Table 12: Structural Equation Model Fit Indices

	χ^2	df	RMSEA	CFI	TLI
Structural model	795	489	.056	.934	.925

Behavioral intention to use CCMM has a positive and significant effect on real use of CCMM (β = .19, $p < .05$). Thus, H1 is supported. Performance expectancy of CCMM has a positive and significant effect on behavioral intention to use CCCM (β = .53, $p < .001$). Thus, H2 is supported. Effort expectancy shows a significant effect on behavioral intention to use CCMM (β = .13, $p < .05$). Thus, H3 is supported. Social influence has no significant effect on behavioral intention to use CCMM (β = .00, $p > .05$); thus, H4 is rejected. Concerning consumer perceived value, utilitarian value has a positive and significant effect on performance expectancy of CCMM (β = .20, $p < .01$). Thus, H5 is supported. Hedonic value has a positive and significant effect on behavioral intention to use CCMM (β = .32, $p < .001$). Thus, H6 is supported. Economic value and environmental value both show no positive and significant effect on behavioral intention to use CCMM (β = .13, p > .05; β = -.06, p > .05). Thus, H7 and H8 both are rejected. Trust has no significant effect on behavioral intention to use (β = .00, p > .05) and privacy concerns have no significant effect on technology trust (β = .01, p > .05). Thus, H9 and H10 are both rejected. Task enablement has a positive and significant effect on behavioral intention to use CCMM (β = .75, p < .001). Thus, H11 is supported.

Table 13: Path Coefficients and Significances

Relationship	**Path coefficient**	**p value**	**Sig.**	**Result**
H1. BI → RU	.19	.010	*	Supported
H2. PE → BI	.53	.000	***	Supported
H3. EE → BI	.13	.037	*	Supported
H4. SI → BI	.00	.961	ns	Rejected
H5. UTT → PE	.20	.006	**	Supported
H6. HED → BI	.32	.000	***	Supported
H7. ECO → BI	.13	.066	ns	Rejected
H8. ENV → BI	-.06	.447	ns	Rejected
H9. TR → BI	.00	.988	ns	Rejected
H10. PC → TR	.01	.244	ns	Rejected
H11. ENA → PE	.75	.000	***	Supported

Note: BI = Behavioral Intention of Use; RU = Real Use; PE = Performance Expectancy; EE = Effort Expectancy; UTT = Utilitarian Value; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental value; SI = Social Influence; TR = Technology Trust; PC = Privacy Concerns; ENA = Task Enablement
* p < .05; ** p < .01; *** p < .001; ns p > .05

In addition, we carried out a mediation analysis with 1000 bootstrap samples (Hayes 2009). The results show three significant mediating effects (the 95% confidence interval [CI] excludes 0; Table 14). First, there is a significant indirect positive effect that runs from performance expectancy to real use via behavioral intention to use (β = .0995, p < .05, 95% CI [.0326; .1664]). Second, there is a significant indirect positive effect that runs from hedonic value to real use via behavioral intention to use (β = .0610, p < .05, 95% CI [.0102; .1119]). Third, there is a significant indirect positive effect that runs from task enablement to real use via performance expectancy and behavioral intention to use (β = .0743, p < .05, 95% CI [.0213; .1272]).

Table 14: Results Mediation Analysis

Mediation	Path coefficient	95% CI		Significant
		Lower	Upper	
PE → BI → RU	.0995	.0326	.1664	Yes
EE → BI → RU	.0239	-.0048	.0525	No
SN → BI → RU	.0000	-.0048	.0525	No
TR → BI → RU	.0000	-.0975	.0980	No
HED → BI → RU	.0610	.0102	.1119	Yes
ECO → BI → RU	.0252	-.0078	.0583	No
ENV → BI → RU	-.0106	-.0436	.0225	No
ENA → PE → BI → RU	.0743	.0213	.1272	Yes
UTT → PE → BI → RU	.0200	-.0086	.0487	No
PC → TR → BI → RU	.0000	-.0012	.0012	No

Note: BI = Behavioral Intention of Use; RU = Real Use; PE = Performance Expectancy; EE = Effort Expectancy; UTT = Utilitarian Value; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; SI = Social Influence; TR = Technology Trust; PC = Privacy Concerns; ENA = Task Enablement

Finally, we did moderation analysis to find moderation effects of the variables gender, age, and experience in our model (see Table 15). First, and concerning gender, we find only one moderation effect between the relationship of utilitarian value and performance expectancy in our model; being a female (b = .43, p < .05) leads to a higher impact of utilitarian value on performance expectancy. Second, we detect one moderation effect of age between the relationship of economic value on behavioral intention; the impact of economic value on behavioral intention to use CCMM decreased with increasing age. Third, and related to prior experience, we find a moderating effect on the relationship between technology trust and behavioral intention; more experience with shared micromobility (b = -.22, p < .05) service leads to a lower impact of technology trust on behavioral intention to use CCMM. Moreover, we find a moderation effect of experience between economic value and behavioral intention; more experience decreases the effect of economic value (b = -.12, p < .05) on the intention to use CCMM. Finally, we find a moderation effect between the relationship of behavioral intention to use on real use behavior; the impact of intention on real use is stronger for respondents with higher prior experience with shared micromobility (b = -3.06, p < .05).

Table 15: Results Moderation Analysis

Moderator		**H1**	**H2**	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**	**H10**	**H11**
Gender	b	1.60	.16	.27	.15	.43	.24	.13	.13	.30	-.06	-.07
	p	.539	.167	.194	.177	.011*	.281	.137	.266	.135	.607	.390
Age	b	.51	-.08	-.20	-.09	-.15	-.19	-.09	-.06	-.10	.01	-.07
	p	.779	.275	.132	.101	.184	.132	.037*	.447	.484	.907	.134
Prior experience	b	3.06	-.08	.01	-.06	.07	.03	-.12	-.06	-.22	-.07	-.06
	p	.039*	.232	.910	.346	.477	.809	.010*	.376	.032*	.277	.166

Note: * p < .05; ** p < .01; *** p < .001

5 Discussion and Contributions

Although the use of shared micromobility is enjoying great interest in the market and public discussion, and despite the growing number of studies in this area, there are to our best knowledge no studies that examine the adoption factors of closed-campus micromobility solutions. Publicly available solutions show disadvantages, like randomly parked vehicles on sidewalks, vandalism, and consumer misbehavior, and are perceived controversially in public opinion. The reasons and causes for these problems are not so much in the vehicles themselves, but in how they are used. Closed-campus micromobility solutions can contribute to higher and better use of shared micromobility and consequently to a reduction in motorized individual transport. However, such closed-campus solutions are still new and little available, although more market activities, as well as research activities, are taking place in this direction. It is important to understand consumers' perceptions and evaluations of such solutions to promote usage and enhance acceptance. For instance, potential users are not familiar with the use of shared micromobility solutions, think they are difficult to use, and do not understand the possible value of such solutions for their daily life. However, experiencing new technological solutions can help create stronger beliefs about the solutions, better comprehending and grasping consumers' perceptions about the product (Kempf, 1999; Smith, 1993). By surveying registered users of DHBW Drive, this research helps to understand factors that influence users' perception of behavioral intention to use a closed-campus micromobility solution.

5.1 Discussion of the Results

Our results are in line with previous findings about the adoption of shared mobility options. The first group of variables is related to performance expectancy, effort expectancy, and task enablement. In line with the literature, perceived performance expectancy has a positive impact on behavioral intention to use (Gao et al., 2019; Kopplin et al., 2021). People in a closed-campus environment are more likely to use micromobility solutions when they perceive the service as performant. Specific to the context, we could demonstrate that this perception is highly related to daily work and task duties, as perceived task enablement has a strong positive effect on performance expectancy in both studies. Moreover, by doing mediation analysis, we show the importance of task enablement and performance expectancy. Both variables turn out to significantly influence not only behavioral intention to use but also real use. Moreover, we support existing research about the link between effort expectancy and behavioral intention. People demonstrate a higher behavioral intention to use the micromobility solution when they perceive the solution as easy to use (Chen & Lu, 2016).

Next, we cannot support the relationship between social influence and behavioral intention to use. Users of DHBW Drive tend not to be influenced by others with the use of the micromobility service. Similar results have been found in previous studies about the adoption of publicly available bike sharing (Gao et al., 2019) and technology adoption in the context of universities (Gunasinghe et al., 2019; Wrycza et al., 2017). Universities have a tradition of promoting independence and freethinking and, therefore, members are less likely to be influenced by others (Skoumpopoulou et al., 2018).

Concerning the four investigated consumer perceived value dimensions, hedonic value shows the strongest significant effect on behavioral intention. People understand CCCM solutions as fun and enjoyable to use, which contributes to their intention to use them (Kopplin et al., 2021). Furthermore, we show that this relationship is influenced by gender, as in our sample we detect a moderation effect, meaning that the influence of hedonic value on behavioral intention is stronger for men. In addition and similar to performance expectancy and task enablement, there is a significant indirect positive effect that runs from hedonic value to real use via behavioral intention to use (Kopplin et al., 2021). Consequently, these three variables seem to be of high importance for real adoption behavior in our sample. Moreover, our analysis does support the relationship between perceived utilitarian value and intention to use (Lyu & Zhang, 2021). Furthermore, we cannot support the relationship between environmental value and intention to use, as there is no significant path coefficient between both variables in the model (Chen, 2019). An explanation could be that DHBW Drive offered e-scooters only and the controversial debate about the sustainability of e-scooter usage (Hollingsworth et al., 2019; Hosseinzadeh et al., 2021) could clarify why the service DHBW Drive was not perceived as green and environmentally friendly by the users. Finally, we cannot support existing research about the economic value of shared micromobility solutions. In contrast to the literature (Christoforou et al., 2021), CCMM users are not significantly influenced in their mobility decision by financial and economic reasons. However, we note that the p value of the path coefficient between economic value and behavioral intention only marginally exceeds the necessary significance level ($p = .061 > 0,05$). Therefore, we still believe that our underlying theoretical reasoning was developed in the right sense, but could not be confirmed by our empirical study. In summary, our analysis confirms that the perceived value of micromobility is manifold for users, and depends on the individual context and setting. Although the relationship between economic value and intention to use the CCMM cannot be conclusively demonstrated in our sample, we want to highlight the moderating effects of age and prior experience with shared micromobility on this relationship. Both age and prior experience negatively affect the relationship, implying that older respondents and respondents with shared micromobility experience are less influenced by economic value in their decision to use the CCMM.

Next, in contrast to the literature (Javadinasr et al., 2022), we cannot support the importance of technology trust and privacy concerns of using shared micromobility solutions. The context of our study could serve again as an explanation. First, the respondents are young and former research indicates that young people are less susceptible to the influence of risk and trust perceptions towards technology (Malaquias & Hwang, 2016). A more general explanation could be that micromobility services have probably reached a stage of market maturity in which trust and privacy concerns in the technology no longer play an important role in acceptance. This argument can be supported by the results of our moderation analysis, as we find a negative moderation effect of prior experience on the relationship between technology trust and behavioral intentions, suggesting that prior shared micromobility experiences reduce the influence of technology trust on behavioral intentions to use CCMM.

Finally, we show significant positive effects of behavioral intention to use on the actual real use, which is in line with the proposition of the UTAUT2 that the stronger the intention to perform the behavior is, the more likely it is that the real use will be performed (Blut et al., 2021; Venkatesh et al., 2012). Furthermore, we show that this relationship is positively moderated by prior experience with shared micromobility, indicating that individuals who have already used shared micromobility services before are more likely to use closed micromobility when they intend to do so.

5.2 Theoretical Contributions

To the best of our knowledge, the present study represents the first empirical analysis that systematically investigates shared micromobility adoption behavior in a professional, closed-campus environment. By enhancing the UTAUT2 model (Venkatesh et al., 2012) with new and rarely investigated key determinants specific to the context and testing our conceptual model, our research has four three main theoretical contributions. First, and based on the well-established UTAUT2 model (Venkatesh et al., 2012), we highlight the relevance of cognitive antecedents of usage intention and real use of a closed-campus micromobility service. Performance expectancy and effort expectancy are both significant antecedents of behavioral intention to use closed-campus micromobility, whereas social influence is not. We thus contribute to the literature by demonstrating that adopting shared micromobility in closed-campus settings is based on rather cognitive than social considerations (Bandura, 1989). Moreover, and specifically for the context, we enhance the model with the cognitive variable drawing from employee enablement theory (Adler & Borys, 1996; Permana et al., 2015) and demonstrate that expected performance is strongly influenced by perceived enablement in daily tasks. The more users perceive the solution as enabling and helpful tool provided by the organization, the more performant the perception will be and the more they intend to use it. We thus contribute to the literature about closed-campus micromobility by demonstrating the importance of perceived enablement in the performance perception of the closed-campus micromobility service.

Second, we show that in addition to cognitive variables of performance and effort expectancy (Venkatesh et al., 2012), specific consumer perceived value dimensions (Holbrook, 1994; Zeithaml, 1988) influence the decision to use the shared micromobility service. Based on existing research, shared micromobility services are said to provide manifold added value to the users (Abduljabbar et al., 2021; Buehler et al., 2021). We show the importance of hedonic value and utilitarian value for the decision to use closed-campus micromobility. However, we could not prove this link for economic value and environmental value. Accordingly, our results contribute to the understanding of antecedents of the adoption of closed-campus micromobility and show that hedonic and utilitarian value (Babin et al., 1994) are important concepts to enhance the behavioral intention to use a closed-campus micromobility service.

Third, and finally, we contribute to the literature on technology adoption research (Blut et al., 2021). Based on the behavioral data provided by DHBW Drive, we demonstrate the positive effect of behavioral intention to use closed-campus micromobility on subsequent real use behavior. This empirical confirmation of the positive causal relationship is important as in the prevailing technology adoption literature this link is rarely tested as either behavioral data is missing or use behavior is measured retrospectively and self-reported (Fisher, 1993; Nenycz-Thiel et al., 2013). This reinforces the relevance of real usage data (e.g., from field laboratories) with technology acceptance models (Blut et al., 2021).

5.3 Managerial Implications

Our research provides managers and potential clients with an overview of the factors that influence behavioral intentions to use closed-campus micromobility services. From the manager’s perspective, it is relevant because it provides recommendations for increasing the intentions to use such services. From the perspective of potential customers, it is relevant because it explains the benefits to users and organizations. Perceived hedonic benefits are a major antecedent of micromobility use, especially for men, as this relationship is moderated by gender. It is essential to highlight this type of benefit in communication by emphasizing how much fun it is to travel with shared micromobility devices. The restriction that most of the devices can exclusively be used by one person at a time does not prevent multiple people from using multiple devices for joint trips. This is also confirmed by the analysis of DHBW Drive usage and geographic data, as students often use the fleet for group rides. In addition, utilitarian benefits play an influential role in the use. Closed-campus micromobility is especially beneficial when it is readily available and enhances routes that previously would have been tedious to walk or cumbersome with other modes of transportation. This is typically the case in urban transportation. Closed-campus micromobility is therefore particularly useful and valuable for organizations that operate in urban areas (e.g., organizations located in downtown areas) or that have such a large geographic area (e.g., university campuses, companies with buildings spread across a central location). Finally, shared micromobility in organizational settings is most effective when it allows people to do their daily routines and work. For example, it is especially beneficial for organizations where users frequently need to move between various locations due to their work and daily routines. DHBW Drive is a distributed downtown organization with multiple buildings and locations. Analysis of actual usage data also indicates that e-scooters are being used by these users, who are experiencing an improvement in their daily activities, and that there is more collaboration since the introduction of the service. Therefore, CCMM providers should focus on organizations, where, due to the daily work, the services improve users' performance. Finally, we want to highlight the moderating effect of prior experience with shared micromobility for marketers. Individuals who have previously used shared micromobility services are less influenced by trust-related decisions and are more likely to use closed micromobility when they intend to do so. Therefore, we suggest promotions that attract inexperienced people to the service and provide them with an opportunity to gain with using micromobility.

6 Limitations and Future Research

Although the results of this study provide significant information, there are some limitations to consider that call for future research. The first limitation is that only registered users of DHBW Drive were surveyed. Individuals who were not aware of the service or who deliberately did not register were absent, which may lead to bias. The model should be validated with inexperienced people who are unaware of such services. This in turn can provide additional insights and improves external validity. Second, one university may not be representative of other organizations. For example, social influence is an established validated UTAUT2 variable but did not turn out to be significant in our setting of a German university. However, it could be important in other settings. Therefore, similar to the first limitation, we recommend further investigations in other organizational settings. Third, the service DHBW Drive is strongly associated with e-scooters, as we did not include other transportation modes in the field laboratory. However, e-scooters are controversial in the public's opinion. Future research should also consider other modes of transportation (e.g., conventional bicycles or electric bikes). Finally, shared e-scooters are a publicly discussed topic and most people have already created one or more images, even if they have not yet used them. Therefore, we suggest that the impact of user experience on perceptions should be a worthwhile future research direction.

7 Summary of the Chapter

This chapter has focused on the main antecedents of the initial adoption and real use of shared micromobility innovations in a closed campus environment of a German university. Therefore, we enhanced the well-established unified theory of acceptance and use of technology (Venkatesh et al., 2012) with constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), and from trust-risk theories, such as trust (Pavlou, 2003) and privacy concerns (Martin & Murphy, 2017). To test the enhanced model, we incorporated both survey and real behavioral data from DHBW Drive, a field laboratory for micromobility at Baden-Wuerttemberg Cooperative State University in Stuttgart, Germany. The results of structural equation modeling reveal that perceived performance expectancy, effort expectancy, task enablement, hedonic value, and utilitarian value are significant antecedents of behavioral intention and that behavioral intention does positively affect real use of our study participants.

While understanding how to encourage and support initial user adoption of a shared micromobility innovation is an important task, the long-term viability of a new product or service additionally depends on the continuity of user behavior. Therefore, the study of factors that influence the continuity of user behavior after initial adoption has become an important topic in marketing and technology application research (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). To promote the continuity of user behavior, the study of consumer satisfaction is fundamental (Bhattacherjee, 2001; Bhattacherjee & Lin, 2015). With this in mind, the focus of the following chapter is to investigate antecedents of consumer satisfaction and its influence on the continuity of user behavior of shared micromobility in closed-campus environments.

Introduction

Chapter 1.
A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Chapter 3.
Satisfaction and Continuance Intention with Closed-campus Micromobility

Chapter 4.
Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Conclusion

Chapter 3.

Satisfaction and Continuance Intention with Closed-campus Micromobility

Abstract

Over the past decade, numerous shared mobility innovations have come to market that are impacting the way people travel and consume transportation (Castellanos et al., 2022), and closed-campus micromobility is one of those shared micromobility innovations. For the long-term viability of such services, it is important for marketers to understand the antecedents of continuance behavior. To do so, we draw on the expectation-confirmation model (Bhattacherjee, 2001) and integrate constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988) and the theory of well-being (Diener et al., 1999; Diener & Chan, 2011) to analyze satisfaction and continuance intention to use the service. We use declarative survey data as well as behavioral data from users (N=234) of DHBW Drive, a field laboratory for micromobility sharing at Baden-Wuerttemberg Cooperative State University Stuttgart, Germany, to test the conceptual model and to investigate the influence of continuance intention on real continuance use of closed-campus micromobility. Our structural equation modeling analysis reveals that subjective well-being has a strong and significant effect on satisfaction with the service, which in turn influences continuance intention to use a closed-campus micromobility service. Furthermore, our analysis confirms that consumers' perceived value in the form of hedonic and economic values are significant and positive antecedents of subjective well-being.

Figure 12: Chapter 3 – Objectives, Methodology, and Publications

OBJECTIVES	• Investigate antecedents of continuance adoption (continued use) of closed-campus micromobility (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011) • Extend ECM (Bhattacherjee, 2001) with new antecedents adopted to the context: consumer perceived value, subjective well-being • Study the influence on real use behavior by incorporating mixed-data approach (survey and behavioral data; Blut et al., 2021)
METHODOLOGY	• Structural equation modeling • 234 users of service DHBW Drive – Survey data: after using the service DHBW Drive (04/11/21-24/11/21) – Behavioral data: after survey completion until end of the service DHBW Drive (28/02/22)
PUBLICATIONS	Schwing, M. (2022). E-Scooters, Perceived Value and Users' Subjective Well-Being: An Empirical Study about Organization-based Shared Micromobility. 2022 American Marketing Association Summer Academic Conference, Chicago (IL), US + Virtual. August 12-14. Targeted Journal: Transportation Research Part F: Traffic Psychology and Behaviour

1 Introduction

Consumers' mobility behavior is changing worldwide. In urban settings, where short-distance mobility is particularly relevant, the shared use of micromobility modes and especially of e-scooters is experiencing explosive adoption (Lang et al., 2022). But although shared micromobility and e-scooters are fast-growing global consumer phenomena, they are also controversial and highly debated topics. Clutters of randomly parked vehicles on sidewalks, risky riding behavior, and vandalism are major issues associated with shared e-scooter usage behavior (Gössling, 2020). Organization-based shared, closed-campus micromobility can overcome problems of publicly available solutions and are deployed in limited areas, such as university or office campuses, only available to the respective campus or organization community (e.g., students, and office employees; Shaheen et al., 2020).

Although, such services have already entered the market and promote themselves as "being the best possible partner for cities while building the safest, most equitable, and most sustainable mobility solution for the communities we serve" (e.g., Spin, 2023), we still know little why communities and organization should provide and users should adopt and use such services. Users' beliefs and attitudes are critical to the adoption of new products and services. While there are various approaches to encouraging user adoption of an innovation, the long-term viability of a new product or service additionally depends on the continuity of user behavior, not just the initial decision to adopt. Therefore, user behavior after technology adoption has become a vital topic in marketing and technology adoption research (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). Although past literature has investigated variables that motivate individuals to use shared micromobility services, it is insufficient because a) is focused on empirically investigating antecedents of initial usage intention, and b) it does rarely account for organization-based, closed-campus systems.

Understanding antecedents of continued use or “continuance intention to use” shared micromobility solutions (in contrast to initial usage intention or “acceptance”) is the goal of this study. With this in mind, we propose an integrated model to examine the role of functional and psychological factors to determine the intention to continue the usage of shared micromobility solutions in an organization-based closed-campus system. Furthermore, using DHBW Drive, a field laboratory for micromobility at the Cooperative State University of Baden-Wuerttemberg (DHBW) in Stuttgart, Germany, as a case study, we analyze not only continuance intention to use but also its impact on real continuance use behavior. Therefore, we theoretically contribute to research in the following ways. First, we enhance the expectation-confirmation model (Bhattacherjee, 2001) by drawing on new and rarely investigated variables specific to the context of shared micromobility use. Recent previous research has shown that the concept of subjective well-being (Diener & Chan, 2011), defined as people’s emotional responses, domain satisfactions, and global judgments of life satisfaction (Diener et al., 1999), is positively correlated with consumer satisfaction and continued technology choice and use (Gupta et al., 2021; Purohit et al., 2022). As shared micromobility modes can help to stimulate physical movement and enhance mental health (Jones et al., 2016; Woodcock et al., 2014) and can improve users’ sense of autonomy and financial stability (Jorgensen et al., 2010; Mouratidis, 2021), we add the concept of subjective well-being to our model. Moreover, shared micromobility is considered to have multiple added values for consumers (e.g., convenient, accessible, sustainable, affordable, and enjoyable urban mobility alternative; Abduljabbar et al., 2021; Buehler et al., 2021), a comprehensive study of the influence of consumers’ perceived value on the decision-making process about continued use can provide valuable insights. Therefore, we add constructs drawing from consumer perceived value (Holbrook, 1994; Zeithaml, 1988). Second, we operationalize and test the model by combining empirical survey data and real behavioral data, which is rare in the adoption research literature (Blut et al., 2021).

From a managerial perspective, the results help inform mobility platform operators and customers (e.g., universities, office campuses, and businesses), policymakers, and transportation planners seeking to improve micromobility adoption and management.

Our article is organized as follows. First, we define the research context of closed-campus micromobility services, provide a review of related literature and then elaborate our conceptual model about the antecedents of continuance intention to use such services. Consequently, we formulate our hypotheses, followed by a description of the methodology and data. We then present and discuss the results. Finally, we highlight the implications for theory and practice, address the limitations of the research, and outline future research directions.

2 Theoretical Background

In the following section we first explain the term closed-campus micromobility (CCCM), provide a theoretical background about the research field and then develop the conceptual model that explains the continuance use of CCMM.

2.1 Closed-campus Micromobility

The term "closed-campus" was first introduced by Shaheen and Chan (2016) in the context of bike sharing systems that "are increasingly being deployed at university and office campuses and are only available to the particular campus community they serve" (Shaheen & Chan, 2016, p. 580). The main difference between closed-campus systems and public shared micromobility solutions is that these services are limited to a specific user group defined by organizational affiliation (e.g., employees of a company, members of a university, users of an office campus), and usage is geographically restricted to an application area. For our further research, we use the term "closed-campus micromobility" (CCMM) to describe a transportation solution that provides access to shared micromobility vehicles that are only available to members of a particular organization. CCMM combines aspects of station-based and limited user groups and represents a new and innovative solution that has also been recognized by the established micromobility providers. In 2022, Spin announced to invest up to $2 Million to support academic research on micromobility in campus environments (e.g., Spin, 2022). Similar to Spin, the University of Colorado is partnering with the micromobility provider Lime to provide non-vehicular travel options for area employees, students, and residents (City of Boulder, 2022). Both examples show that micromobility providers, campus operators, and cities are interested in understanding and enhancing micromobility adoption in organizational-based, closed-campus environments.

2.2 Literature Review

Previous studies on shared micromobility have used various theories and analyses to examine initial adoption intention. As stated in the introduction, these theories are not specific to post-adoption behavior and can be insufficient to explain continuance intention for shared micromobility. While understanding initial usage intention is an important first step toward realizing long-term success, the long-term viability of shared micromobility solutions in our society and their eventual success depends additionally on the continuity of user behavior. Therefore, we focus our literature review, on studies that investigate continuance intention as a dependent variable rather than adoption intention to use (see Table 16).

Most of the reviewed studies have used the TAM (technology adoption model; Davis, 1989) to examine the factors that contribute to the intention to continue using micromobility services. Although the TAM was originally developed to examine users' initial usage adoption of new technologies, products, and services, there is also research stating that it can be used to formulate the continued use of a product or service after adoption (Liao et al., 2009). Accordingly, Shao and Liang (2019) draw on TAM and linear regression analysis to show that perceived usefulness, perceived ease of use, and consumer innovation, have a significantly positive impact on the intention to continue using shared bicycles in China. Moreover, Kim and Kim (2020) enhanced TAM to examine the intention to continue using bike sharing in China for their analysis. They reported that overall perceived value and trust have significant positive impacts on consumers' continuance intention, while financial risk negatively affects the intention to continue using the service (Kim & Kim, 2020). Similarly and based on TAM, Li and Lin (2022) show that perceived usefulness, perceived ease of use, descriptive social norms, and injunctive social norms are positively related to the continuance intention of dockless bike sharing users. Lastly, Javadinasr et al. (2022) extended the TAM and substantiate that the most salient factor determining users' decisions is perceived usefulness, followed by perceived reliability, social influence, perceived ease of use, variety seeking, and perceived enjoyment. Moreover, Peng et al. (2019) incorporated TCT (Technology Continuance Theory; Liao et al., 2009) which is based on TAM and corroborated that perceived usefulness, satisfaction, and attitude positively and perceived risk negatively impact the reuse intention of 559 users of bike sharing in China. Besides the literature that draws on TAM, we found three articles that do not draw on a technology adoption model. Zhang et al. (2021) proposed a structural equation model with bike sharing purchase decision-making involvement, traveler participation, and traveler's perceived value as independent variables and bike sharing willingness to use as the dependent variable. Jayasimha et al. (2021) conducted a 2x2 between-subject experiment in the context of e-scooter sharing to explore contamination fear. Liang et al. (2022) used the four-phase loyalty theory (Oliver, 1999) as a framework to examine users' loyalty toward shared bicycles. Moreover, they demonstrate that green perceived value and trust of users positively relate to usage intention and loyalty (Liang et al., 2022). Finally, we found two articles that draw on the expectation-confirmation model (ECM; Bhattacherjee, 2001). Wang et al. (2020) incorporated the ECM to study the continuance intention for shared micromobility service in the form of public bike sharing in China. The results from SEM indicated that perceived usefulness, service quality, riders' habits, and overall satisfaction were the most important factors positively influencing users' intentions to continue bike sharing (Wang et al., 2020). Moreover, based on ECM, Shao et al. (2020) show that continuance intention to use public bike sharing in China was mainly influenced by satisfaction and by perceived usefulness.

Concerning investigated context, most of the studies were done in Asian countries and in the context of public bike sharing. Only two studies investigated e-scooter sharing (Javadinasr et al., 2022; Jayasimha et al., 2021) and only one study was done in a Western country (Javadinasr et al., 2022). Javadinasr et al. (2022) surveyed 2,126 shared e-scooter users in Chicago, United States, and show that the most influencing factor on users' continuance intention is perceived usefulness, followed by perceived reliability (availability of e-scooters at the times and places they are needed, especially for mandatory trips). The strong focus on bike sharing in Asian countries can be explained. In Asian countries, the bicycle has always been the main means of transport and part of the mobility culture (Chevalier et al., 2019; Ye, 2022). Western countries are mostly car-centric cultures, where the car is used as the main means of transport for mobility purposes of all kinds (BCG, 2020; Lukasiewicz et al., 2022). To realize the full potential of shared micromobility, it is essential to understand and promote the motivations for switching from motorized individual transport (in the form of the private car). Therefore, more research should be conducted on the adoption of shared micromobility in Western, car-centric countries.

Regarding investigating characteristics, many independent variables have been investigated in the reviewed studies. Studies, which draw on TAM, usually investigate perceived usefulness, perceived ease of use, and attitude as main antecedents of the intention to continue using the service and enhance the model with additional variables. These variables may range from general personal beliefs of the respondents (e.g., environmental concerns, variety seeking), to psychological perceptions towards the sharing service (e.g., service and bike quality), to psychological perceptions (e.g., health and environmental benefits). In terms of the dependent variables, loyalty and continuance intention are the variables of choice. Loyalty to a particular product or service is directly related to continued sales of products or services and can be defined as a high level of commitment to a repurchase intention in the future, which is the opposite of the customer switching to a competitor (Oliver, 1999). Thus, in most research, loyalty and continuance intention are understood as synonyms, with a high probability of continuance intention being understood as a high expression of loyalty. However, similar to the initial intention to adopt, a high intention to continue to use a service or product does not lead to real loyalty or continued real use. No study did investigate real continuance use as a dependent variable. However, understanding real use, as a consequence of behavioral intentions, is an important interest in adoption behavior research (Blut et al., 2021). This leads over to the next point of sampling. To give reasonable statements of antecedents of continuance intention and real continuance use, research should investigate samples where user experience is available. However, some studies did also take non-users into account. For example, Chen (2016) did a multi-group analysis based on a modified TAM version to indicate differences between users and non-users of Youbike bike sharing in Taipei City, Taiwan. Their results indicate that perceived fun turns out to be a strong predictor for continuance intention for both groups, with a stronger effect for the user group. However, they did not test for significant differences in path coefficients, and therefore the differences can only be interpreted at a descriptive level.

In summary, our literature review shows that understanding continuity behavior in the use of shared micromobility services has recently gained attention in academia. Although the number of studies in this area is increasing, we find that there are still serious gaps to contribute. First, and with regard to investigated context, most of the studies were done in the context of public micromobility sharing. No article investigated the new and innovative form of shared micromobility in closed-campus environments. Moreover, most of the articles focus on the investigation of bike sharing. Only two articles did investigate the highly debated application of e-scooter sharing (Javadinasr et al., 2022; Jayasimha et al., 2021). Furthermore, the two articles were the only articles that were conducted in Western countries. In conclusion, research would benefit from more investigations of e-scooter sharing in Western countries and from investigating new and innovative applications (like closed-campus settings; Shaheen et al., 2020) to overcome dark side issues of existing publicly available solutions (Gössling, 2020).

Second, most of the research draws on TAM (Davis, 1989) to investigate the continuance intention to use shared micromobility. Although the TAM was originally developed to examine users' initial usage, there is also research stating that it can be used to formulate the continued use of a product or service (Liao et al., 2009). While the TAM assumes that user behavior is mainly influenced by the perception of utilitarian reasons (e.g., perceived usefulness and ease of use; Davis, 1989), other research postulates that examining consumer satisfaction, resulting from the use of the service is fundamental to understanding the continuity of user behavior (Bhattacherjee, 2001; Bhattacherjee & Lin, 2015). Only three articles did investigate satisfaction as an important antecedent of continuance intention (Peng et al., 2019; Shao et al., 2020; Wang et al., 2020). However, all three articles were conducted in the context of publicly available bike sharing services and Asian countries (i.e., China). To further investigate the significance of satisfaction for continuity behavior and to promote continued use of shared micromobility, research would benefit from more investigations about recently discussed e-scooter sharing applications in car-centric Western countries.

Third, existing research has examined various aspects of the continued use of shared micromobility. However, we found important aspects that are missing in understanding the perceptions, motivations, and barriers specific to the context of closed-campus micromobility and recent applications of shared micromobility in general. Consistent with the recommendations of a recent meta-analysis on technology adoption (Blut et al., 2021), the literature would contribute from more enhancements of established behavioral models to examine less or understudied cognitive, and affective variables. Shared micromobility is highlighted for its multiple added values for consumers (Holbrook, 1994), which can range from utilitarian benefits (e.g., more convenient and faster than public transport or walking) to economic benefits (e.g., time and money saving) to environmental benefits (e.g., more sustainable and environmentally friendly than a private vehicle) to hedonic benefits (e.g., enjoyment/relaxation). However, we have not found a comprehensive analysis of these different consumer value dimensions that can influence the consumers' perception of satisfaction and continuity behavior. In addition, research would benefit from examining variables that currently receive attention in academic discussions. For example, subjective well-being is currently an important and often studied topic in different contexts of acceptance research (Diener et al., 1999; Knight et al., 2009; Wei & Gao, 2017), as it is said to be positively correlated with satisfaction and consumers' technology choices and usage (Diener & Chan, 2011; Gupta et al., 2021). As the use of shared micromobility can help to maintain personal mobility and reduce the negative environmental impacts of mobility behavior (Jones et al., 2016; Lindsay et al., 2011; Woodcock et al., 2014), investigating subjective well-being can help to understand why people should continue using shared micromobility services.

Fourth, and finally, while most of the articles examined perceptions of actual users to understand continuance intention, none examined actual continuance real use as a dependent variable. However, understanding real use as a consequence of behavioral intentions is an important concern in adoption research that, for a variety of reasons (e.g., lack of real behavioral data), has received insufficient coverage in the existing literature (Blut et al., 2021). Therefore, it would be an essential contribution to research to examine not only the intention to continue use but also the real continuance use.

Table 16: Overview of Research about Shared Micromobility Continuance Intention

Study	Context	Theory	IV	DV	Methodology
Chen (2016)	Public bike sharing	TAM, TPB	Attitude, Behavioral control, subjective norm, Perceived usefulness, Green value, Perceived pleasure	Loyalty	261 users (YouBike) and 261 non-users in Taipei City, Taiwan; Multi-group CB-SEM (AMOS)
Peng et al. (2019)	Public station-based bike sharing	TCT	Confirmation, Perceived risk, Perceived usefulness, Perceived ease of use, Satisfaction, Attitude	Continuance intention	559 users and non-users in Nanjing, China; Multi-group CB-SEM (AMOS)
Shao and Liang (2019)	Public bike sharing	TAM	Perceived usefulness, Perceived ease of use, Consumer innovation, Social norm behavior	Continuance intention	532 users in China (Panel); Ordinal linear regression
Jamšek and Culiberg (2020)	Public bike sharing	TAM	Perceived usefulness, Perceived ease of use, Subjective norm, Sustainable extraversion, Bike quality	Loyalty	185 users (Bicikelj) in Slovenia; SEM
Kim and Kim (2020)	Public dockless bike sharing	TAM	Perceived usefulness, Perceived ease of use, Perceived enjoyment, Perceived value, Trust in a service provider, Financial risk, Privacy risk	Continuance intention	224 users (Hellobike, Mobike, Ofo) in China; PLS-SEM (SmartPLS)
Shao et al. (2020)	Public bike sharing	ECM	Perceived usefulness, Satisfaction, Confirmation, Service quality	Continuance intention	437 users (Mobike, Ofo) in China (panel); PLS-SEM (SmartPLS)
Wang et al. (2020)	Public bike sharing	ECM	Perceived usefulness, Perceived ease of use, Habit, Service quality, System quality, Satisfaction	Continuance intention	376 users in China, CB-SEM (AMOS)
Jayasimha et al. (2021)	Public e-scooter sharing	-	Contamination fear, resource sufficiency, Responsibility perception	Continuance intention	167 users in India; Online experiment; Regression analysis (PROCESS)

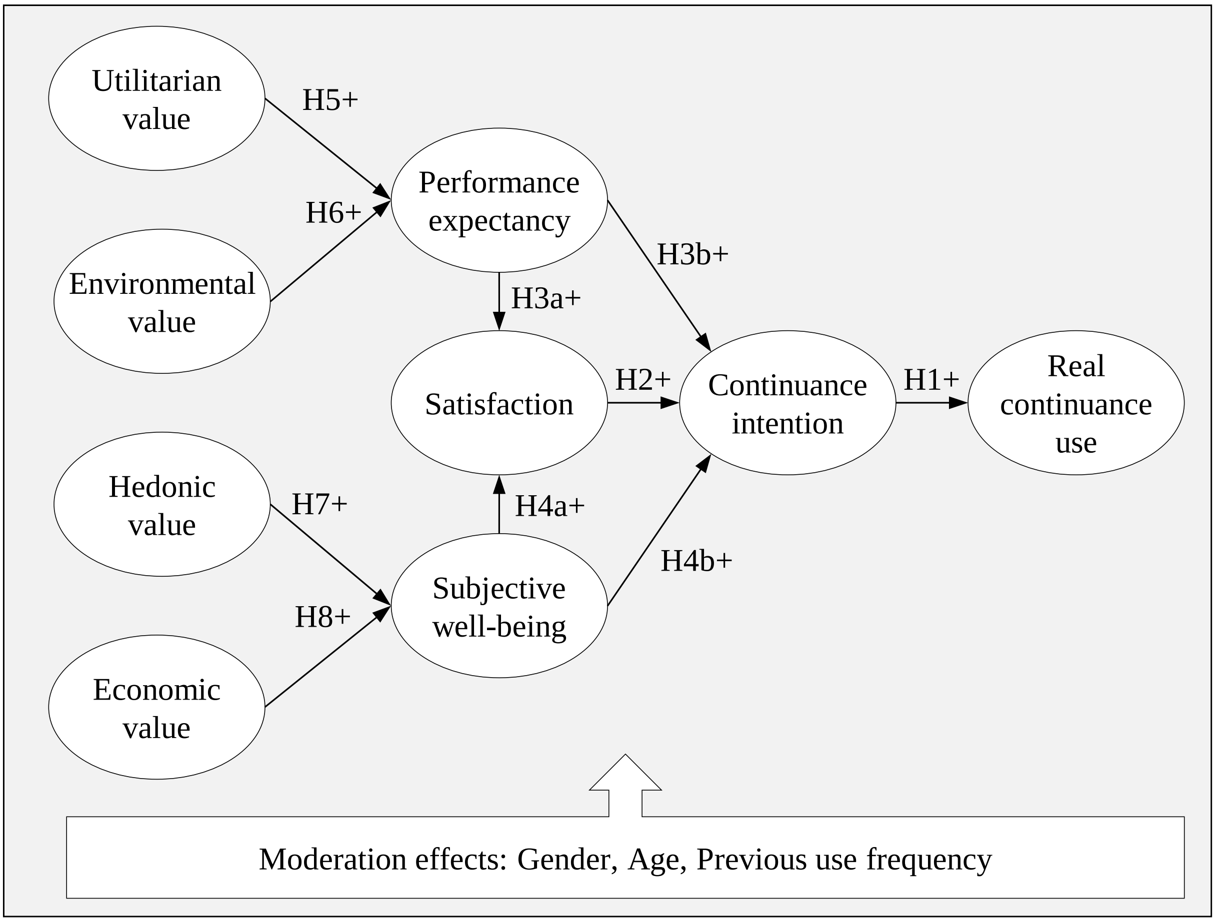
Zhang et al. (2021)	Public bike sharing	-	Purchase decision involvement, Customer participation, Emotional value, Functional value, Security value	Continuance intention	622 respondents in Xi'an, China (Panel); CB-SEM (AMOS)
Javadinasr et al. (2022)	Public e-scooter sharing	TAM	Perceived usefulness, Perceived ease of use, Social influence, Variety seeking, Perceived enjoyment, Perceived reliability	Continuance intention	2,126 users (Lime, Spin, Bird) in Chicago, United States; PLS-SEM (SmartPLS)
Li and Lin (2022)	Public dockless bike sharing	TAM	Environmental concern, Descriptive social norms, Injunctive social norms, Perceived usefulness, Perceived ease of use	Continuance intention	369 users (Mobike, Hellobike) in Hangzhou, China; PLS-SEM (SmartPLS)
Liang et al. (2022)	Public station-based bike sharing	Four-phase Loyalty Theory	Perceived value, Trust, Usage intention	Loyalty	345 users (Youbike) in Taipei City, Taiwan; CB-SEM (AMOS)

2.3 Conceptual Model and Hypotheses

For our research, we choose the expectation-confirmation model (ECM; Bhattacherjee, 2001) as it is a post-adoption model, which is specific and appropriate to explain the intention to continue using shared micromobility. Moreover, the ECM has already been used to investigate shared micromobility continuance intention in public settings (Shao et al., 2020; Wang et al., 2020). Bhattacherjee (2001) proposed the ECM as an adaptation of the expectation-confirmation theory (ECT, Oliver, 1980) which holds that satisfaction and perceived usefulness are key predictors of repurchase intention. Perceived usefulness refers to the perceived functional benefits of a product or service, and satisfaction is the evaluation of the user's experience with the product or service. Since its development, expectation-confirmation models have been utilized to study consumers' repeat purchase decisions and continued usage decisions and have been broadly used to examine the continuance intention of users for technology-oriented products and services, for example, smartwatches (Nascimento et al., 2018), mobile apps (Tam et al., 2020), mobile health (mHealth) technology (Chiu et al., 2021; Wu et al., 2022). Moreover, the ECM has been frequently used in the recent past to investigate the intention to continue using shared-consumption services, e.g., ride sharing (Arteaga-Sánchez et al., 2020; Si et al., 2022).

We contribute to the literature about user behavior after technology adoption (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011) by adding new theories and associated constructs. First, we incorporate the construct of subjective well-being (Diener et al., 1999; Diener & Chan, 2011). The concept of subjective well-being is defined as emotional reactions, domain satisfaction, and global assessments of life satisfaction (Diener et al., 1999), and research indicates a positive association of subjective well-being on consumer satisfaction and continued technology choice and use (Gupta et al., 2021; Purohit et al., 2022). As the use of shared micromobility can positively stimulate physical exercise, mental health, and economic situation (Jones et al., 2016; Jorgensen et al., 2010; Mouratidis, 2021), we investigate subjective well-being as a variable in our model. Second, we add variables drawing from the theory of consumer perceived value (Holbrook, 1994; Zeithaml, 1988). Consumer perceived value is the overall assessment of the consumption benefits on perceptions of what is received and what is given (Zeithaml, 1988). As shared micromobility is deemed to provide several added benefits to the user (e.g., convenient, accessible, sustainable, affordable, and enjoyable urban mobility alternative; Abduljabbar et al., 2021; Buehler et al., 2021), we add four constructs drawing from consumer perceived value (Holbrook, 1994; Zeithaml, 1988) to provide a comprehensive study of the influence of consumers' perceived value on the decision-making process about continued use. Our conceptual model and the hypotheses are formalized in Figure 13 and will be explained in the following sections.

Figure 13: Conceptual Model about Continuance Use of Closed-campus Micromobility



2.3.1 ECM, Continuance Intention

In the expectation-confirmation model, continuance intention refers to motivational factors which influence a given behavior that follows an initial acceptance decision and is influenced by the initial use and usage experience (Bhattacherjee, 2001). Therefore, continuance intention should be understood as the main antecedent of real continuance use of a given product or service because the stronger the continuance intention to perform the behavior is, the more likely it is that real continuance use will be performed. Based on our literature review, we could not find any study that systematically investigated this relationship. Although most of the studies have made sure to include only actual users (rather than "unaware" non-users), they have all been survey-based. Consequently, they were unable to demonstrate whether the continuance intention really influences the real continuance use behavior. Thus, we hypothesize:

Hypothesis 1. Continuance intention positively influences real continuance use of CCMM.

2.3.2 ECM, Satisfaction

Satisfaction was initially defined in the context of job performance as “a pleasurable or positive emotional state resulting from the appraisal of one’s job” (Locke, 1976, p. 1300). Oliver (1980) extended this definition in developing the ECT to the consumption context as “the summary of psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumer’s prior feeling about the consumption experience” (Oliver, 1981, p. 29). Accordingly, consumer satisfaction can be understood as the overall evaluation of a consumer’s consumption experience with products or services over a period of time (Anderson et al., 2004). ECM proposes that satisfaction is the major positive antecedent of continuance intention of a product or service. This relationship has been empirically proven in previous studies in the context of shared micromobility, e.g., public station-based bike sharing (Peng et al., 2019; Wang et al., 2020), as the satisfaction of the users with shared micromobility services will be inclined to continue using it. Thus, we hypothesize:

Hypothesis 2. Satisfaction positively influences the continuance intention of CCMM.

2.3.3 ECM, Performance Expectancy

Performance expectancy refers to “users’ perceptions that using a new technology will improve their performance” (Venkatesh et al., 2003, p. 447). Performance expectancy pertains to perceived usefulness (Venkatesh et al., 2003), which was initially defined in the TAM as “the degree to which a person believes that using a particular system enhances his or her job performance” (Davis, 1989, p. 320). In the development of the ECM, perceived usefulness was a substantial factor that influences both the satisfaction and the continued use of technologies (Bhattacherjee, 2001). Performance expectancy and perceived usefulness are similar concepts that are also sometimes used synonymously (Bhattacherjee & Lin, 2015): However, in certain situations, the use of performance expectancy as a measurement is more appropriate (Bhattacherjee et al., 2012). The more recent performance expectancy focuses specifically on the extent to which a user believes that using the technology will improve their performance in terms of productivity, effectivity, and efficiency, and is, therefore, more appropriate for professional environments (Venkatesh et al., 2003). As we are investigating closed-campus micromobility services, which are usually deployed in a professional, task-related environment (e.g., university and office campuses), we use performance expectancy to measure the utilitarian perceptions of users of a closed-campus micromobility service. Moreover, former research has proven the positive relationship between performance expectancy and continuance intention (e.g., e-scooter sharing; Javadinasr et al., 2022, bike sharing; Shao & Liang, 2019): the more users perceive the shared micromobility solution as useful for, e.g., traveling between places or achieving things in daily life, the more likely they are for continued usage. Similarly, existing literature has investigated the positive impact of perceived usefulness on satisfaction (Peng et al., 2019; Shao et al., 2020; Wang et al., 2020): consumers who detect products or services as useful are more likely to be satisfied with it (Bhattacherjee, 2001). For instance, Wang et al. (2020) demonstrate that the more a bike sharing service is perceived as performant and useful in terms of efficiency and effectivity, the more the users express satisfaction with the service. Thus, we hypothesize:

Hypothesis 3a. Performance expectancy positively influences satisfaction with a CCMM.

Hypothesis 3b. Performance expectancy positively influences the continuance intention of CCMM.

2.3.4 Subjective Well-being

Subjective well-being has been given increasing amounts of attention in the last few years, and it has been researched in the field of sociology, psychology, and even social media (Diener et al., 1999; Knight et al., 2009; Wei & Gao, 2017). Subjective well-being can be defined as “a broad category of phenomena that includes people’s emotional responses, domain satisfactions and global judgments of life satisfaction” (Diener et al., 1999). Existing research has shown that subjective well-being while using a product or service is positively correlated with satisfaction and consumers’ technology choices and usage (Diener & Chan, 2011) as people feel satisfied and intrinsically motivated and continue to do anything that makes them feel good. Consequently, the more users feel positive mental, psychological, and physiological beliefs about a technology, the higher the level of satisfaction and using a technology will be. The positive relationship between subjective well-being through the use of new products and continuance intention has been investigated and proven in different new technology research fields, e.g., smartwatch usage (Chuah, 2019) and mobile payment services (Purohit et al., 2022). Similarly, research has demonstrated that a higher level of subjective well-being through the use of a new technology, will result in a higher level of user satisfaction with the technology (e.g., smartwatch usage; Gupta et al., 2021). Moreover, research about shared micromobility states that micromobility usage can help to maintain personal mobility, can reduce the negative environmental impact of mobility behavior, can substitute short car journeys, and consequently can promote health and well-being (Jones et al., 2016; Lindsay et al., 2011; Woodcock et al., 2014). Therefore, if consumers develop positive feelings towards a closed-campus micromobility service that contributes to subjective well-being, this should increase a) users’ satisfaction with the service and b) their continuance intention to use the service. Thus:

Hypothesis 4a. Subjective well-being with CCMM positively influences satisfaction with CCMM.

Hypothesis 4b. Subjective well-being with CCMM positively influences the continuance intention of CCMM.

2.3.5 Consumer Perceived Value

Consumer perceived value is defined as "the overall assessment of the utility of a product based on perceptions on what is received and what is given" (Holbrook, 1994; Zeithaml, 1988, p. 14), and has always been a focus of consumer behavior research, and previous studies have examined the constituent attributes of perceived value and their influences on consumer acceptance decisions. Perceived value, considered a complex concept, has been operationalized as a multidimensional construct to illustrate its complexity (Babin et al., 1994; Sheth et al., 1991; Sweeney & Soutar, 2001). Studies about shared micromobility reveal that shared micromobility provides several substantial benefits to users (Abduljabbar et al., 2021; Sanders et al., 2020; Smith & Schwieterman, 2018): utilitarian (e.g., more convenient and practical than walking or motorized individual vehicle), economic (e.g., time and money saving), environmental (e.g., contributing to a better and more sustainable transportation behavior), hedonic benefits (e.g., enjoyment and fun to use).

First, utilitarian value refers to consumers' perception of whether their needs are met in functional terms or whether adoption behavior contributes to utilitarian performance (Babin et al., 1994). Micromobility modes provide utilitarian value as they are a quick and easy-to-use choice for short-distance mobility demands and are more convenient and flexible to use than other transportation alternatives (e.g., Sanders et al., 2020). For instance, Lyu and Zhang (2021) show that utilitarian value in terms of traffic performance positively impacts the perceived usefulness of bike sharing (Lyu & Zhang, 2021; Ye, 2022). Thus, we hypothesize:

Hypothesis 5. Perceived utilitarian value positively influences performance expectancy of CCMM.

Second, environmental value refers to the consumers' perceptions about whether using a service or product improves the environmental performance in specific areas of life, and includes an assessment of the sustainability of the used product (Chen, 2016; Flores & Jansson, 2021). As shared micromobility is promoted for its ecological benefits and is considered an important part of more sustainable future mobility, we argue that perceived environmental value positively affects shared micromobility users' performance expectancy. For instance, Chen (2016) investigate how the environmental value of bike sharing influences perceived usefulness and conclude a positive effect for both users and non-users. Hence, we hypothesize:

Hypothesis 6. Perceived environmental value positively influences performance expectancy of CCMM.

Third, hedonic value refers to the users' overall judgments of the experiential and emotional benefits of using a product or service (Babin et al., 1994). Hedonic benefits are more subjective and result more from consumer aesthetics, exploration, fun, and entertainment than from task completion (Meyer-Waarden & Cloarec, 2022). Concerning the use of shared micromobility, several studies have highlighted the role of hedonic value. For example, Chen (2016) documents perceived enjoyment as a key construct influencing bike sharing continuance intention. Similarly, Kopplin et al. (2021) investigated a significant positive relationship between perceived enjoyment and the intention to adopt an e-scooter. Moreover, research about new mobility services shows that hedonic value is positively related to the perception of subjective well-being (e.g., autonomous vehicles; Meyer-Waarden & Cloarec, 2022, bike sharing; Ma et al., 2018). As subjective well-being concludes mental, psychological, and physiological beliefs with a technology, we derive that hedonic value expressed by joy and fun using the service should contribute to these beliefs. Thus, we hypothesize:

Hypothesis 7. Perceived hedonic value positively influences subjective well-being with CCMM.

Fourth, economic value refers to the consumers' overall judgments about the costs and benefits of using a product or service, and when the benefits of use exceed the costs, the economic value is positive (Venkatesh et al., 2012). Research has shown that using sharing-based mobility services can produce economic benefits for consumers (Arteaga-Sánchez et al., 2020; Barnes & Mattsson, 2017). When the use of shared micromobility services is combined with other modes of transportation, people can avoid using or owning a personal vehicle (especially expensive passenger cars; Sanders et al., 2020), which in turn can reduce ownership costs. If the cost-benefit ratio improves compared to previous or alternative transportation options, people save money and improve their financial situation. Studies have demonstrated a positive relationship between income and subjective well-being (Ferrer-i-Carbonell, 2005; Jorgensen et al., 2010). We expect that when economic value is perceived as positive by the users, it should contribute to financial subjective well-being. Therefore, we hypothesize:

Hypothesis 8. Perceived economic value positively influences subjective well-being with CCMM.

2.3.6 Moderating Variables

A moderating variable is considered an element that systematically influences either the form or strength of the relationship between an endogenous and exogenous variable (Baron & Kenny, 1986; Sharma et al., 1981). In understanding the phenomenon of technology service adoption, previous research has highlighted individual personal differences that may play a role (Saeed & Abdinnour-Helm, 2008; Sun & Zhang, 2006; Venkatesh et al., 2012). For instance, gender is a critical personal factor within the category of demographic variables (Chiu et al., 2005; Gefen & Straub, 1997; Zhou et al., 2014). Moreover, previous studies have shown that age is an important factor that has received attention in research on the adoption and use of new technologies, products, and services (Chatterjee, 2021; Molinillo et al., 2021; Wu et al., 2020).

Finally, studies have shown that previous use frequency can be an important moderator for the decision to continue using a product or service (Hamilton et al., 2011; Molinillo et al., 2021). Therefore, we include gender, age, and use frequency as moderators in this study.

3 Methodology

3.1 DHBW Drive – a Field Laboratory for Closed-campus Micromobility

DHBW Drive was a field laboratory for shared closed-campus micromobility at Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany, and represents the first successful micromobility sharing system in a closed-campus environment of a German university. With the service, members of the university (approx. 7,000 students and 400 staff) could move between 5 university sites in downtown Stuttgart. In total, a fleet of 70 e-scooters was free-of-charge available and could be rented and parked at defined stations via an app, customized for the field laboratory and available for Android and iOS smartphones. At the stations, the e-scooters were charged using an in-house developed charging concept. Over the duration of the operation, from October 2020 to February 2022, more than 2,200 persons were registered (with a share of 95% of students), more than 12,200 bookings were made, and a total of more than 38,600 km were traveled.

3.2 Sample Characteristics

Our sample is based on an online survey conducted among registered users of DHBW Drive, emailed to, at the time, 1,567 registered people. 441 users completed the survey from 04/11/2021 to 24/11/2021. The survey included one reversed item as well as one direct-query attention check (i.e., “I am not paying attention at all in this survey. Please tick ‘Fully disagree’”) to detect inattentive respondents and increase statistical power (Abbey & Meloy, 2017). 23 respondents failed the attention check, which represents an acceptable loss rate of

5.2%. After the deletion of the inattentive respondents, 418 responses remained for statistical analysis. The survey included the "prefer not to answer" (PNA) response option (Albaum et al., 2010; Sischka et al., 2022). As for our statistical analysis only complete responses without missing values could be used, 231 responses were valid for statistical analysis. 95.0% of our respondents were students and 5.0% were employees of the university. The gender distribution of our respondents was 22.0% females and 78.0% males (see Table 17). Furthermore, the average (median) age was 22.06 (20) years. Our sample is thus not representative of the German population. However, the age and function distributions can be understood as representative of a German university, which is a target group for closed-campus micromobility. Furthermore, it can be argued that samples from younger populations facilitate comparability and represent a promising segment for the use of new forms of mobility, as younger generations tend to be more enthusiastic about new technologies, products, and services (Ashraf et al., 2014; Barbosa et al., 2019; Mcmillan & Morrison, 2006; Meyer-Waarden & Cloarec, 2022).

Table 17: Sample Description

Variable	Value	Total	Relative [%]
Age	19 and younger	55	23.8
	20 – 29	165	71.4
	30 – 39	3	1.3
	40 – 49	2	.9
	50 – 64	6	2.6
Gender	Male	180	77.9
	Female	51	22.1
Function	Student	218	94.4
	Staff / Lecturer	13	5.6
Total		231	100

3.3 Measurement Instruments

All measurement scales are adapted from previous studies (see Table 18). Responses were collected based on a seven-point Likert scale (1 = fully disagree, 7 = fully agree).

Continuance intention (e.g., “CI1: I intend to continue rather than discontinue use of the service DHBW Drive.; CI2: My intentions are to continue using the service DHBW Drive rather than use another mode of transportation.; CI3: If I could, I would like to stop using the service DHBW Drive.”) and satisfaction (e.g., “SAT1: I am satisfied with the use of the service DHBW Drive.; SAT2: I am overall pleased with the service DHBW Drive.; SAT3: The service DHBW Drive makes me feel contented.; SAT4: I find the service DHBW Drive delightful.”) were both measured with scales from Bhattacherjee (2001).

To measure performance expectancy (e.g., “PE1: I find the service DHBW Drive useful in my daily life.; PE2: Using the service DHBW Drive increases my chances of achieving important things.; PE3: Using the service DHBW Drive helps me get things done more quickly.; PE4: Using the service DHBW Drive increases my productivity.”), we used the scale from Venkatesh et al. (2012).

Subjective well-being was measured with three items (e.g., “SWB1: By using the service DHBW Drive, my quality of life improves.; SWB2: By using the service DHBW Drive, my overall well-being improves.; SWB3: By using the service DHBW Drive, I feel happier.”) which we adapted from a scale of Meyer-Waarden and Cloarec (2022).

To measure utilitarian value (e.g., “UTT1: The service DHBW Drive makes it easier for me to reach my destinations.; UTT2: The service DHBW Drive makes my journeys convenient and more practical.; UTT3: The service DHBW Drive makes my journeys quicker.”), we adapted a scale from Meyer-Waarden (2013). To measure hedonic value (e.g., “HED1: Using the service DHBW Drive is fun.; HED2: Using the service DHBW Drive is enjoyable.; HED3: Using the service DHBW Drive is very entertaining.”), we used the scale from Venkatesh et al.

(2012). Economic value (e.g., “ECO1: I can save money by using the service DHBW Drive.; ECO2: Using the service DHBW Drive can improve my economic situation.; ECO3: Using the service DHBW Drive benefits me financially.”) and environmental value (e.g., “ENV1: The use of the service DHBW Drive is environmentally friendly.; ENV2: I feel that I am contributing to a sustainable environment by using the service DHBW Drive. ENV3: The service DHBW Drive is an example of a green service.”) were both measured with a scale taken from Barnes and Mattsson (2017).

To reduce the likelihood of bias from the common-method (CMB), we followed two approaches. First and based on the CMB marker technique of Richardson et al. (2009), we spatially separated the dependent variables (i.e., continuation intention) from the independent variables by inserting a theoretically irrelevant marker variable between the two survey sections (Lindell & Whitney, 2001; Malhotra et al., 2006). Second, CMB exists when either a) a common factor emerges from the data or b) a single factor explains most of the variance (Podsakoff et al., 2003). To test for CMB, we used Harman’s single-factor test. The single factor explained 38% of the total variance. Since the total variance extracted by a single factor did not exceed the recommended threshold of 50%, CMB was not a problem in our survey (Harman, 1976).

To quantify real continuance use in our model, we incorporated behavioral data from the backend system of the service DHBW Drive. We used four indicators: count of bookings [#], sum of driven distance [km], sum of booking time [min], and sum of travel time [min]. The sum of the travel time is the difference of the sum of the booking time minus the sum of the parking time, as the DHBW Drive vehicles could be parked during the time of use. As time span for real continuance use, we chose all bookings made after answering the survey until 28/08/2022. To ensure data protection and anonymity, survey data were linked with behavioral data through a two-step process.

3.4 Assessment of the Measurement Instrument

We conducted a confirmatory factor analysis to test the reliability and validity of the measurement instruments by using the software R 3.6.1 and the lavaan package (Rosseel, 2012). To assess convergent validity, we checked for average variance extracted (AVE), which should exceed the minimum threshold of .5 for all constructs (see Table 18; Hair et al., 2019, p. 9). A second aspect of convergent validity refers to indicator loadings that should exceed the recommended threshold value of .708 (Hair et al., 2019, p. 8). To achieve acceptable convergent validity, we removed indicators below the threshold from the initially specified measurement instrument (i.e., CI2, SAT3, and PE4). However, we did not remove the indicator CI3, as AVE for continuance intention was acceptable above the recommended threshold. To assess reliability, we checked all latent constructs for Cronbach's α. All latent constructs showed values above the recommended threshold of .7 (see Table 18; Hair et al., 2019, p. 8).

Table 18: Scales, Reliability (α), Convergent Validity (AVE), and Loadings

Constructs, items, and sources	**α**	**AVE**	**Load.**
Economic value (Barnes & Mattsson, 2017)	.89	.75	
ECO1: I can save money by using the service DHBW Drive.			.75
ECO2: Using the service DHBW Drive can improve my economic situation.			.88
ECO3: Using the service DHBW Drive benefits me financially.			.94
Hedonic value (Venkatesh et al., 2012)	.89	.72	
HED1: Using the service DHBW Drive is fun.			.93
HED2: Using the service DHBW Drive is enjoyable.			.85
HED3: Using the service DHBW Drive is very entertaining.			.78
Utilitarian value (Meyer-Waarden, 2013)	.87	.69	
UTT1: The service DHBW Drive makes it easier for me to reach my destinations.			.82
UTT2: The service DHBW Drive makes my journeys convenient and more practical.			.88
UTT3: The service DHBW Drive makes my journeys quicker.			.80

Environmental value (Barnes & Mattsson, 2017)	.89	.75	
ENV1: The use of the service DHBW Drive is environmentally friendly.			.86
ENV2: I feel that I am contributing to a sustainable environment by using the service DHBW Drive			.83
ENV3: The service DHBW Drive is an example of a green service.			.90
Performance expectancy (Venkatesh et al., 2012)	.94	.85	
PE1: I find the service DHBW Drive useful in my daily life.			.86
PE2: Using the service DHBW Drive increases my chances of achieving important things.			.96
PE3: Using the service DHBW Drive helps me get things done more quickly.			.94
PE4: Using the service DHBW Drive increases my productivity.			-
Subjective well-being (Meyer-Waarden & Cloarec, 2022)	.91	.79	
SWB1: By using the service DHBW Drive, my quality of life improves.			.91
SWB2: By using the service DHBW Drive, my general well-being improves.			.95
SWB3: By using the service DHBW Drive, I feel happier.			.81
Satisfaction (Bhattacherjee, 2001)	.85	.66	
SAT1: I am satisfied with the use of the service DHBW Drive.			.90
SAT2: I am overall pleased with the service DHBW Drive.			.83
SAT3: The service DHBW Drive makes me feel contented.			-
SAT4: I find the service DHBW Drive delightful.			.79
Continuance intention (Bhattacherjee, 2001)	.73	.67	
CI1: I intend to continue rather than discontinue use of the service DHBW Drive.			.93
CI2: My intentions are to continue using the service DHBW Drive rather than use another mode of transportation.			-
CI3: If I could, I would like to stop using the service DHBW Drive. (inverted)			.62
Continuance use (CU)	.71	.87	
CU1: Total number of bookings [#]			.97
CU2: Total driven distance [km]			.93
CU3: Total booking time [min]			-
CU4: Total moving time [min]			-

Discriminant validity was evaluated by the heterotrait-monotrait (HTMT) ratio. As all HTMT ratios showed good scores below the recommended threshold of .85 (Henseler et al., 2015), we assume good discriminant validity for our measurement model (see Table 19).

Table 19: Discriminant Validity (HTMT Ratios)

Construct	M	SD	CU	CI	SAT	PE	SWB	UTT	ENV	HED	ECO
CU	3.21	8.03									
CI	6.37	.86	.12								
SAT	5.4	1.26	.09	.64							
PE	3.14	1.69	.36	.35	.27						
SWB	4.29	1.59	.30	.53	.50	.71					
UTT	5.53	1.24	.17	.57	.54	.54	.53				
ENV	4.73	1.45	.08	.25	.21	.38	.36	.42			
HED	6.10	1.12	.06	.55	.73	.28	.46	.56	.16		
ECO	4.61	1.81	.13	.28	.22	.52	.43	.53	.44	.25	

Note: CU = Continuance use; CI = Continuance Intention; SAT = Satisfaction;
PE = Performance Expectancy; SWB = Subjective Well-being; UTT = Utilitarian Value;
ENV = Environmental Value; HED = Hedonic Value; ECO = Economic Value

Overall, the measurement model achieved acceptable fit according to the usual fit indices: the chi-square/df ($\chi2$/df) was less than 2.5; the comparative fit index (CFI) and Tucker-Lewis Index (TLI) were greater than .90; the root mean square error of approximation (RMSEA) was not greater than .08 (Anderson & Gerbing, 1988). The fit indices of the measurement model are summarized in Table 20.

Table 20: Measurement Model Fit Indices

	χ^2	df	RMSEA	CFI	TLI
Measurement model	389	239	.052	.966	.957

4 Results

To test our conceptual model and the established hypotheses, we performed structural equation modeling (SEM) using the software R 3.6.1 and the lavaan package (Rosseel, 2012). Similar to the measurement model, we assessed the structural equation according to the usual fit indices. Table 21 summarizes the fit indices for the structural equation model, which again achieved good fit: $\chi 2/df < 2.5$; RMSEA < .08, CFI > .90, and TLI > .90. Table 22 shows the results of the SEM and presents the estimated direct path coefficients and p values that indicate the direct effect of one variable on another variable.

Table 21: Structural Equation Model Fit Indices

	χ^2	df	RMSEA	CFI	TLI
Structural model	633	259	.079	.915	.902

Continuance intention to use has no significant effect on real continuance use ($\beta = .13$, $p > .05$). Thus, H1 is not supported. Satisfaction has a positive and significant effect on continuance intention to use ($\beta = .51$, $p < .001$). Thus, H2 is supported. Performance expectancy has neither a significant effect on satisfaction ($\beta = -.09$, $p > .05$) nor on continuance intention ($\beta = .08$, $p > .05$). Thus, both H3a and H3b are rejected. Subjective well-being has a significant effect on satisfaction ($\beta = .54$, $p < .001$) and on continuance intention ($\beta = .23$, $p < .01$). Thus, both H4a and H4b are supported. Utilitarian value has a positive and significant effect on performance expectancy ($\beta = .48$, $p < .001$). Thus, H5 is supported. Similarly, environmental value has a positive and significant effect on performance expectancy ($\beta = .18$, $p < .01$). Thus, H6 is supported. Hedonic value has a positive and significant effect on subjective well-being ($\beta = .36$, $p < .001$). Thus, H7 is supported. Finally, economic value has a positive and significant effect on subjective well-being ($\beta = .38$, $p < .001$). Thus, H8 is supported.

Table 22: Path Coefficients and Significances

Relationship	Path coefficient	p value	Sig.	Result
H1. Continuance intention → Real continuance use	.13	.075	ns	Rejected
H2. Satisfaction → Continuance intention	.51	.000	***	Supported
H3a. Performance expectancy → Satisfaction	-.09	.194	ns	Rejected
H3b. Performance expectancy → Continuance intention	.08	.173	ns	Rejected
H4a. Subjective well-being → Satisfaction	.54	.000	***	Supported
H4b. Subjective well-being → Continuance intention	.23	.002	**	Supported
H5. Utilitarian value → Performance expectancy	.48	.000	***	Supported
H6. Environmental value → Performance expectancy	.18	.009	***	Supported
H7. Hedonic value → Subjective well-being	.36	.000	***	Supported
H8. Economic value → Subjective well-being	.38	.000	***	Supported

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; ns $p > .05$

In addition, we carried out a mediation analysis with 1000 bootstrap samples (Hayes 2009) and continuance intention as the dependent variable. We chose continuance intention as the dependent variable because real continuance use is not significantly influenced in our model (see Table 23). Significant mediating effects occur when the 95% confidence interval [CI] excludes the value of 0. First, there is a significant indirect positive effect that runs from subjective well-being to continuance intention via satisfaction ($\beta = .2770$, $p < .05$, 95% CI [.0683; .1431]). Second, there are significant indirect positive effects that run from hedonic value to continuance intention via subjective well-being ($\beta = .0853$, $p < .05$, 95% CI [.0362; .0130]) and from economic value to continuance intention via subjective well-being ($\beta = .0888$, $p < .05$, 95% CI [.0375; .0153]). Third, there are significant indirect positive effects that run from hedonic value to continuance intention via subjective well-being and satisfaction ($\beta = .1009$, $p < .05$, 95% CI [.0355; .0313]) and from economic value to continuance intention via subjective well-being and satisfaction ($\beta = .1050$, $p < .05$, 95% CI [.0316; .0432]).

Table 23: Results Mediation Analysis

Mediation	Path coefficient	95% CI		Significant
		Lower	Upper	
PE → SAT → CI	-.0438	.0471	-.1361	No
SWB → SAT → CI	.2770	.0683	.1431	Yes
UTT → PE → CI	.0394	.0443	-.0474	No
ENV → PE → CI	.0147	.0168	-.0182	No
HED → SWB → CI	.0853	.0362	.0130	Yes
ECO → SWB → CI	.0888	.0375	.0153	Yes
UTT → PE → SAT → CI	-.0209	.0221	-.0642	No
ENV → PE → SAT → CI	-.0078	.0089	-.0252	No
HED → SWB → SAT → CI	.1009	.0355	.0313	Yes
ECO → SWB → SAT → CI	.1050	.0316	.0432	Yes

Note: CI = Continuance Intention; SAT = Satisfaction; PE = Performance Expectancy; SWB = Subjective Well-being; UTT = Utilitarian Value; ENV = Environmental Value; HED = Hedonic Value; ECO = Economic Value

Finally, to test for moderating effects of age, gender, and use frequency in our model, we did a moderation analysis (see Table 24). First, and concerning gender, we do not find any moderation effects. Second, and with regard to age, we find a moderation effect of continuance intention on real continuance use; with increasing age, the stated intention to continue using the service shows less impact on real continuance use ($b = -2.62$, $p < .05$). Moreover, there is a moderating effect of age on the relationship between environmental value and performance expectancy; older respondents do see less impact of environmental value on performance expectancy ($b = -.47$, $p < .01$). To conclude with the moderation effects of age, we find a moderation effect between the relationship of hedonic value and subjective well-being; with increasing age, the impact of hedonic value on subjective well-being decreases ($b = -.36$, $p < .01$). We detect the same effect in the relationship between economic value and subjective well-being; with increasing age, the impact of economic value on subjective well-being decreases ($b = -.26$, $p < .01$). Finally, we checked for the moderation effect of use frequency before the survey. Therefore, we used the count of bookings [#] before participating in the survey and then divided the sample into two equal groups (i.e., median split in high-frequency group and low-frequency group). We detect two moderating effects of use frequency. First, there is a positive moderation effect on the relationship between environmental value and performance expectancy; the impact is stronger for high-frequency user ($b = .34$, $p < .05$). The same moderation effects appear for the relationship between utilitarian value and performance expectancy; with a stronger impact for the group of high-frequency users ($b = .35$, $p < .05$).

Table 24: Results Moderation Analysis

Moderator		H1	H2	H3a	H3b	H4a	H4b	H5	H6	H7	H8
Gender	b	-.28	-.02	.04	-.02	.11	.03	-.12	-.27	-.01	-.25
	p	.874	.855	.780	.804	.405	.695	.496	.120	.971	.057
Age	b	-2.62	.00	-.01	-.03	-.10	-.04	-.20	-.47	-.36	-.26
	p	.021*	.959	.921	.642	.280	.472	.166	.001**	.007**	.022*
Use frequency	b	-.31	-.09	-.16	-.12	-.11	-.12	.35	.34	-.16	.09
	p	.803	.256	.111	.055	.242	.060	.028*	.018*	.345	.395

Note: * p < .05; ** p < .01; *** p < .001

5 Discussion

5.1 Main Findings

According to previous research, shared micromobility is emerging as a promising urban transportation mode, particularly for its potential to reduce reliance on private vehicle use for short-distance travel (Abduljabbar et al., 2021). Hence, an important question in facilitating the use of micromobility services is: What motivates people to use such services on a continuous basis? The results of our study should help to answer this critical question in a meaningful way. In this regard, our results are mostly consistent with previous knowledge from existing research about the continuance intention to use shared micromobility. However, we also obtain contradictory results and, moreover, we develop new arguments.

First, the fundamental idea of the ECM is that peoples’ continuance intentions are mainly affected by satisfaction with the used product or service. Based on the ECM, we demonstrate that satisfaction is an essential antecedent of continuance intention to use a shared micromobility in the form of a closed-campus solution (Bhattacherjee, 2001). In our model, satisfaction is the strongest significant predictor of continuance intention: The more users of a closed-campus micromobility service are satisfied with the service, the more likely they are to continue using it. Hence, it is crucial to understand and investigate possible factors that positively influence satisfaction with the service.

Second, and in contrast to the general proposition of the ECM, in our sample performance expectancy does not exert a statistically significant positive impact, neither on satisfaction nor on continuance intention. Comparing our results to existing studies, the lacking support for performance expectancy contradicts the prevailing literature on technology adoption usage, although this phenomenon has been discovered in previous work (Boakye et al., 2014; Shang et al., 2005; Terzis & Economides, 2011). Accordingly, different explanations can be given. One plausible reason for the lacking support of for performance expectancy is that after initial adoption users may implicitly believe that the used product or service is useful (Boakye et al., 2014). Hence, the impact of performance expectancy on satisfaction and continuance intention diminishes after initial adoption, relinquishing its strength to other, previously less relevant factors (e.g., subjective well-being). Another plausible reason could be that our sample (95% of students) focuses more on personal use rather than professional use. For professional work-related use, usefulness in the sense of productivity, effectiveness, and efficiency, is relevant to keeping one’s job or getting promoted. For personal private use, the evaluation of usefulness is often based more on the satisfaction of one’s own curiosity or relates to the individual satisfaction of other aspects (Shang et al., 2005). However, our findings are comparable to findings from Jamšek and Culiberg (2020) and Chen (2016) about loyalty to bike sharing programs, where sustainable, green usefulness did not influence loyalty to the service. The question emerges as to why loyalty does not derive from the belief that there are sustainable benefits to using public bike sharing systems. According to Chen (2016), one explanation might be the current perception of public bike sharing and shared micromobility in general, which depending on the individual setting may be seen as a transit mode with limited ability for transportation. Based on this argument, another explanation, why in our sample no significant impact of performance expectancy can be detected, might be the infrastructural setting of DHBW Drive. DHBW Drive was a station-based micromobility system where members of DHBW could rent vehicles at five mobility hubs, located at the university's main locations in the Stuttgart city center. However, due to local constraints, some locations and buildings of the university could not be covered, making it less convenient and likely for certain user groups to use the services. Therefore, due to the lack of access, there may have been a reduced assessment of performance expectancy among affected respondents, which in turn could explain the insignificant positive impact of performance expectancy on satisfaction and continuance intention in our sample.

Third, our analysis shows that subjective well-being resulting from the use of a closed-campus micromobility service is a strong and significant predictor of satisfaction with the service and the decision to further use the service. Our results are in line with recent research in transformative consumer research about the influence of subjective well-being on behavior and satisfaction (e.g., smartwatches; Gupta et al., 2021) and continuance intention to use new technology-enabled products and services (e.g., mobile payments; Purohit et al., 2022). The use of shared micromobility, such as bike sharing, is known as a sustainable form of transportation that can tackle the "last mile" transit issue in urban areas (Zhu et al., 2022). Moreover, former research about the outcomes of micromobility has proven that micromobility modes can help to maintain personal mobility, can substitute short car journeys, and consequently promote physical health and well-being (Jones et al., 2016; Lindsay et al., 2011; Woodcock et al., 2014). We investigate and empirically test the relationship between subjective well-being, satisfaction, and continuance intention in the context of shared micromobility solutions. The more users feel that they can improve mental, psychological, and physiological beliefs through the use of the shared micromobility service, the higher the satisfaction with the service and the higher the continuance intention to use the service will be. The confirmation of these positive relationships is particularly interesting because performance expectancy no longer shows a significant influence in our sample. Consequently, it can be concluded that future research about the adoption of shared micromobility should consider perceived subjective well-being as an important predictor.

Fourth, our analysis confirms that the perceived value of micromobility is manifold for users, as all four investigated perceived value dimensions show significant impacts on either performance expectancy or subjective well-being. Regarding performance expectancy, we can demonstrate that utilitarian value and environmental value show both a significant positive influence. Our results are in line with former research about the influence of perceived utilitarian value on performance expectancy (Lyu & Zhang, 2021; Ye, 2022). Shared micromobility modes can provide utilitarian value by being a quick and easy-to-use choice for short-distance mobility needs, and by being more convenient and flexible to use than other transportation alternatives, and consequently influence the performance expectancy of the service. Moreover, this relationship is moderated by the frequency of prior use; in our sample, high-frequency users appreciate the utilitarian value more in their evaluation of performance expectancy. Moreover, our investigation highlights that performance expectancy is also influenced by the individual evaluation of the sustainability of the transportation mode, as environmental value turns out to positively influence the perception of the usefulness of the service (Chen, 2016). If users consider the service to be sustainable and ecologically beneficial to satisfy their individual mobility needs, this will also have an impact on the performance expectancy of the service. Furthermore, this relationship is moderated by the frequency of prior use, as in our sample high-frequency users assign higher environmental value in their performance expectancy assessment. This result is interesting as shared micromobility is controversially discussed in terms of sustainability. Although studies have strongly suggested that micromobility can reduce or even replace the use of private vehicles (Smith & Schwieterman, 2018; Wang et al., 2022), some studies raise concerns about direct environmental benefits (Hollingsworth et al., 2019). This discussion can influence the mixed and polarized perception of users, to what extent shared micromobility is environmentally friendly and consequently perceived as a useful mobility mode.

Moreover, we demonstrate that hedonic value has a significant positive effect on subjective well-being. Our results are in line with former research about the influence of hedonic value on subjective well-being (Ma et al., 2018; Meyer-Waarden & Cloarec, 2022; Zhang et al., 2017). Micromobility is perceived as an enjoyable transportation mode and, according to existing research, this perception is positively related to the perception of mental, psychological, and physiological beliefs with a technology. When people perceive using an organization-based micromobility service as fun, joyful, or relaxing, these feelings contribute to subjective well-being with the service. However, this perception is moderated by age, with older people being less influenced by hedonic values in the evaluation of subjective well-being. Finally, we show that subjective well-being is positively influenced by perceived economic value. Our research confirms the previous finding about economic benefits for consumers of shared micromobility. For example, when shared micromobility is understood as one component of multimodal mobility behavior, and is consequently used with other modes of transport (e.g., public transport) (e.g., public transport), people can avoid using and even owning a personal vehicle (especially expensive passenger cars; Sanders et al., 2020). A study about innovative micromobility devices showed that, when using micromobility in a multimodal mobility mix, users could shift about 5,000 car-km per year to public transport and save time on last-kilometer trips and private vehicle parking costs (Zirn et al., 2018). Moreover, improved short-travel connectivity can save time and can improve accessibility compared to private vehicles or walking, which in turn can save money and can contribute to consumers' financial subjective well-being (Lyu & Zhang, 2021). In line with existing literature, our results demonstrate: when users can save money and perceive the service as economically beneficial, these positive feelings will also contribute to their subjective well-being. However, this perception can be influenced by the age of the users. Because our investigation was conducted in an academic setting, most of the respondents were students. Students typically have little or no income. Based on our moderation analysis, we conclude that the influence of economic value on subjective well-being decreases with age.

Finally, we investigated the relationship between continuance intention and real continuance use. Based on our survey sample and the behavioral use data provided by the DHBW Drive backend system, we can show a nearly significant relationship. In this matter, we want to note that the significance value of 8.1% is close to the significance limit of 5.0%. Research on criteria for selecting and interpreting significance levels shows that the usual significance threshold of 5.0% is not only not sacred, but that the selection of a significance level should be understood as a process (Labovitz, 1968; Nelson et al., 1986; Nickerson, 2000). Research argues that depending on research design, e.g., sample size (Labovitz, 1968; Nelson et al., 1986), level of control (Labovitz, 1968; Nickerson, 2000), and plausibility of alternatives (Kim & Ji, 2015; Labovitz, 1968), the significance level should be selected and interpreted. For instance, Labovitz (1968) argues that larger significance levels of 10% can be used with smaller sample sizes, lower levels of controls, and in research settings where alternative explanations are plausible. Given that our sample size is N = 231, that the data collection period for the dependent variable continuance use included two winter periods (November 2021 to February 2022), and that most of the respondents experienced online teaching due to the COVID-19 pandemic, we conclude that there are at least some reasonable explanations why some registered users were unable to use the service even they intended to. Accordingly, we conclude that, although we could not demonstrate a significant relationship at the commonly used significance level of 5%, continuance intention has a positive impact on real continuance use. Spoken in practical words, the more users intend to continue to use a closed-campus micromobility service, the more they will use it. Moreover, as the moderation analysis findings suggest, this relationship is negatively affected by the age of users, as in our sample increasing age displays a negative moderation effect on the impact of stated continuation intention on real continuance use of the service DHBW Drive.

5.2 Theoretical Contributions

In summary and to the best of our knowledge, the current article is the first empirical investigation of the continuance intention of organization-based closed-campus micromobility. Furthermore and by enhancing the expectation-confirmation model (Bhattacherjee, 2001) constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988) and the theory of well-being (Diener et al., 1999; Diener & Chan, 2011), our research contributes to theory in the following ways.

First, we contribute to transformative consumer research (Davis et al., 2016; Zeng & Botella-Carrubi, 2023) and enhance the ECM (Bhattacherjee et al., 2012) with the variable of subjective well-being (Diener et al., 1999). By doing so, we highlight the importance of affective perceptions in the form of subjective well-being (Diener et al., 1999) and its effect on satisfaction, and continued use behavior (Bhattacherjee, 2001) in the context of closed-campus micromobility. Based on our literature review, we are the first to examine these relationships in this particular context. And since in our model subjective well-being is a significant predictor of satisfaction and continuance intention, but performance expectancy is not, we show that in certain situations the perception of improved subjective well-being may be more important than improved performance. The more subjective well-being users expect when using a closed-campus micromobility service, the more they will develop positive feelings and satisfaction with the service, and the more they should intend to use this technology.

Second, we enhance the ECM with constructs drawing from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988) to comprehensively investigate their effects in the process of continued use behavior. Shared micromobility services are highlighted for providing multiple added values to their consumers (Abduljabbar et al., 2021; Buehler et al., 2021). We highlight the four different consumer perceived value dimensions (namely hedonic, economic, environmental, and utilitarian value) as significant antecedents of subjective well-being and performance expectancy of closed-campus micromobility services. In terms of subjective well-being, we demonstrate that both hedonic value (Babin et al., 1994) and economic value (Venkatesh et al., 2012) positively influence the perception of subjective well-being (Diener et al., 1999). The more users perceive the service as a fun and enjoyable mode of transportation, the better they will evaluate the mental, psychological, and physiological benefits of the service in terms of their own subjective well-being (Ma et al., 2018; Zhang et al., 2017). Moreover, if the use of a micromobility service improves the cost-benefit ratio compared to previous or alternative transportation options, people develop positive feelings about the service in terms of their personal subjective well-being (Jorgensen et al., 2010). In addition to the relationships with subjective well-being, we can demonstrate that utilitarian value and environmental value are relevant predictors of the service's perceived performance expectancy. The more users perceive the service as a convenient and practical means of transportation (Lyu & Zhang, 2021; Ye, 2022), the more they will perceive it as an improvement in terms of efficient and effective travel. In addition, we confirm the influence of green perceptions (Chen, 2016; Flores & Jansson, 2021) on performance expectancy: the better the users perceive the service as a sustainable and environmentally friendly mobility option, the stronger the expectation regarding the performance improvement will be.

Third, and finally, we contribute to the field of marketing and technology adoption research literature (Bhattacherjee & Premkumar, 2004; Blut et al., 2021; Venkatesh et al., 2011) by investigating not only continuance intention but also real continuance use behavior. In line with the recommendations of a recent meta-analysis about technology adoption behavior (Blut et al., 2021), we empirically investigate the effect of continuance intention on real continuance use (Blut et al., 2021). Thanks to the DHBW Drive field lab, which provided us with this scarcely accessible real behavioral data, we link survey data with behavioral data in our model. Therefore, we contribute to the literature by empirically assessing the causal relationship between survey-measured continuance intention to use the closed-campus micromobility service and real continuity use behavior, which was measured with behavioral data from DHBW Drive. Although our results exceed the mostly applied significance level of .05 (5%), the, in social science, accepted significance level of .10 (10%) is reached (Labovitz, 1968; Nelson et al., 1986; Nickerson, 2000), confirming that there is a significant positive effect on continuance intention on real continuance use of closed-campus micromobility. This result underlines the relevance of real-world behavioral data (e.g., from field laboratories) for technology acceptance models, and can therefore be considered as an additional methodological-theoretical contribution.

5.3 Managerial Contributions

Our conceptual model provides managers and potential customers with an overview of the factors that influence the intention to further use shared micromobility in an organization-based, more professional, closed-campus context. From a management perspective, it is relevant because it provides recommendations for sharing providers on how to market and communicate such services. From the perspective of potential customers, it is relevant because it explains the benefits for users and organizations. Coming from ECM, we propose that satisfaction with the service is a relevant predictor of obtaining high-use acceptance. According to our model and results, satisfaction with shared micromobility service is not just a simple equation of performance expectancy in terms of mobility from A to B but is influenced by several deep-rooted factors. Therefore, marketers and possible customers should stop seeing shared micromobility only as a useful mode of transportation for short-distance travel that supports tackling the first-and-last-mile problem. Shared micromobility can have manifold added value and can contribute to the subjective well-being of users.

Our empirical analysis suggests that subjective well-being plays an essential role in service usage. Regardless of this finding, the subjective well-being of members should always be a concern for the organization. Therefore, the provision of a closed-campus micromobility service by organizations should also be understood as a measure to increase the overall satisfaction and well-being of organizational members. Thus, it is important to highlight the various benefits that positively influence the perception of subjective well-being. Perceived hedonic value through the use of the services was rated highest in our sample (see construct means in Table 19). Micromobility modes are a joyful alternative to other transportation modes like public transport, walking, or private car. Marketing should highlight these benefits. In addition, closed-campus micromobility is most effective regarding economic value when it is perceived as cost-efficient for users. DHBW Drive is a service for a distributed downtown organization with multiple buildings and locations. Analysis of actual behavioral data also indicates that there is more collaboration since the introduction of the service and that e-scooters are also used for leisure time (e.g., enjoying lunch together). Therefore, organizations should not also see the directly measurable benefits against the potential costs of such services, but also these benefits that are hard to measure. In terms of hedonic and economic value, older users tend to place a lower priority on these benefits in their assessment of subjective well-being. Therefore, we recommend using specific promotions to emphasize these two benefits even for older respondents.

In addition, utilitarian and environmental benefits should be highlighted to enhance the perception of performance expectancy. First, shared micromobility is especially beneficial when it is convenient and quick to use and enhances routes that previously would have been tedious to walk or cumbersome with other modes of transportation. This frequently applies to organizations that operate in urban areas (e.g., organizations located in downtown areas) or that have such a large geographic area (e.g., university campuses, companies with buildings spread across a central location). Second, perceived environmental value shows to be important: thus, a closed-campus micromobility service should also be seen as an example of how to provide sustainable, innovative, and shared micromobility. High-frequency users are more likely to appreciate utilitarian and environmental values in their evaluation of performance expectancy. Therefore, we recommend actively promoting use (e.g., offering trial periods) so that users can use the service to experience the practical benefits of the service.

6 Limitations and Future Research

Although the results of this study provide significant information, there are some limitations to consider. First, the time period for measuring real continuance use is limited because the data collection started after the survey was answered (04/11/2021 to 24/11/2021) and ended with the closing of the project (28/02/2022). Considering the University's Christmas break and the winter season (unfavorable weather and light conditions), a reasonable explanation emerges why a high level of continuance intention possibly did not lead to a high level of real continuance use. Second, the sample size is relatively small and comes from a German university. As we offered the "prefer not to answer" (PNA) response option (Albaum et al., 2010; Sischka et al., 2022) in our survey, all cases with missing values could not be included in the structural equation modeling process (case wise deletion). Moreover, one university may not be representative of other organizations. Therefore, future research should also consider surveying members of organizations in different settings. Third, DHBW Drive is strongly associated with e-scooters, which are controversial in the public eye. Future research should also consider other micromobility modes of transportation (e.g., conventional bicycles or electric bikes). Fourth, the model could be enhanced with additional variables that are barriers and potentially decrease subjective well-being, such as types of risks (e.g., safety concerns).

7 Summary of the Chapter

This chapter has focused on the satisfaction and continuance behavior of shared micromobility innovations in a closed campus environment of a German university. Therefore, we enhanced the expectation-confirmation model (Bhattacherjee, 2001) with constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), and the theory of well-being (Diener et al., 1999; Diener & Chan, 2011) to analyze satisfaction and continuance intention to use the service. For model testing, we incorporated both survey and real behavioral data from DHBW Drive, a field laboratory for micromobility at Baden-Wuerttemberg Cooperative State University in Stuttgart, Germany. The results reveal that subjective well-being has a significant effect on satisfaction with the service, which in turn influences continuance intention to use. Furthermore, we confirm that consumers' perceived value in the form of hedonic and economic values are positive predictors of subjective well-being.

However, innovative technologies, products, and services continue to emerge and evolve (Venkatesh et al., 2021). Accordingly, research calls for investigating temporal issues of adoption behavior and for considering the importance of changing predictors depending on individual user experience in the adoption process (Blut et al., 2021; Venkatesh et al., 2021). Characterized as a publicly debated issue, this continuous evolution in product and service design also applies to shared micromobility services (Lazarus et al., 2020), where people may have already formed an opinion without ever having used such a service. In addition, following a recent meta-analysis on technology adoption research (Blut et al., 2021), future research would benefit from increased research on outcomes. With this in mind, the following chapter investigates the longitudinal effects of user experience on antecedents and possible outcomes of closed-campus micromobility.

Introduction

Chapter 1.
A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Chapter 3.
Satisfaction and Continuance Intention with Closed-campus Micromobility

Chapter 4.
Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Conclusion

Chapter 4.

Dynamic Adoption and Outcomes of Shared Micromobility – A Longitudinal Study based on User Experience

Abstract

Recent research about technology and service adoption highlights the need for investigating the changing importance of predictors over time and calls for investigating temporal issues in the adoption and marketing process (Blut et al., 2021; Venkatesh et al., 2021). In this regard, we analyze the longitudinal effects of user experience on antecedents and outcomes of the use of shared micromobility in a closed-campus environment. Based on the unified theory of acceptance and use of technology (UTAUT2; Venkatesh et al., 2012) and regulatory focus theory (Avnet & Higgins, 2006; Higgins, 1997), we establish a model and add context-specific constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), theory of well-being (Diener et al., 1999; Diener & Chan, 2011) and social identity theory (Ashforth & Mael, 1989). To check for longitudinal effects of user experience, we use a two-wave within-subject survey design with two independent samples: Study 1 is based on an age- and gender-representative sample of inexperienced testers (N=234, short-term experience); Study 2 is a sample of shared micromobility users of DHBW Drive (N=149, long-term experience). To test for longitudinal user experience effects, we use the evolutional path modeling approach for panel data (Roemer, 2016) in partial least square structural modeling. Our results reveal that performance expectancy and task enablement are stable predictors of usage intention, which do

not change over time. In contrast, we find that hedonic value is an important antecedent before user experience. However, its importance decreases as user experience increases. Moreover, we find that perceived economic and environmental values are stable antecedents, but depend on the sample and user segment studied. Concerning consequences and outcomes, we highlight the role of subjective well-being, which turns out to be an important and stable outcome. Finally, we show that organizational identification is a significant outcome before user experience, but is not significant in both samples after user experience.

Figure 14: Chapter 4 – Objectives, Methodology, and Publications

OBJECTIVES	• Investigate longitudinal within-subject effects of user experience on antecedents and outcomes of closed-campus micromobility (Venkatesh et al., 2006; Venkatesh et al., 2021; Blut et al., 2021) • Extend UTAUT2 with new variables adopted to the context: consumer perceived value, task enablement, organizational identification, subjective well-being • Study differences of perceptions depending on short-term and long-term experience effects (Blut et al., 2021; Venkatesh et al., 2021)
METHODOLOGY	• Evolution model for panel data approach in partial least square structural equation modeling • Two-wave within-subject survey design – Survey data Study 1 (short-term experience): 234 participants (external persons) – Survey data Study 2 (long-term experience): 149 users of DHBW Drive
PUBLICATIONS	Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2022). How E-Scooters enhance Identification with your Organization? An Empirical Study about Closed-campus Micromobility Innovations. AU Virtual International Conference 2022 on “Entrepreneurship & Sustainability in Digital Era”, Virtual, October 21. Schwing, M., Kuhn, M., & Meyer-Waarden, L. (2023). Understanding the Dynamic Adoption and Outcomes of Shared Micromobility - a Longitudinal Study based on User Experience. 2023 Academy of Marketing Science Annual Conference, New Orleans (LA), US, May 17-19. Targeted journal: Journal of the Academy of Marketing Science

1 Introduction

All over the world, air pollution, noise, and congestion have become significant problems that deeply affect the quality of life in urban areas and have led to a paradigm shift in the mobility sector. Shared mobility services are on-demand services that reduce reliance on private motorized individual transport, provide a more flexible and sustainable means of transportation, and consequently change consumers' mobility behavior. In this new mobility situation, shared micromobility services are experiencing significant growth and adoption. The most popular form of shared micromobility is e-scooter sharing (e.g., Spin), which provides short-distance travel options, particularly for first- and last-mile trips in urban settings. In this regard, shared micromobility is seen as an important part of a future car-free mobility mix, along with public transportation, and walking. Since 2015, stakeholders have invested more than $5.7 billion in micromobility start-ups and, consequently, shared e-scooters, bicycles and other modes of micromobility have conquered cities around the world (McKinsey & Company, 2019). However, the public has met the introduction of shared micromobility with both enthusiasm and skepticism, as cities have struggled with unforeseen outcomes such as forms of irresponsible riding, cluttering, or vandalism (Gössling, 2020).

One way to overcome problems of publicly available solutions is to apply micromobility in pre-delineated environments. Such pre-delineated solutions are referred to as closed-campus micromobility systems that are deployed in limited, most often organizational or professional environments and are only available to the respective community (e.g., university, office campus, residential quarter; Shaheen & Chan, 2016). While publicly accessible micromobility services have proliferated, with operators offering solutions in cities around the world, the number of closed-campus micromobility solutions is also increasing. In June 2022, the well-known shared micromobility platform Spin announced that they will invest up to $2 million in a partnership with Michigan State University and The University of Utah to optimize transportation outcomes in campus environments (Spin, 2022). Similar to Spin, since 2021 the shared micromobility provider Lime is partnering with the city of Boulder and the University of Colorado to deploy 200 e-scooters and to provide non-vehicular travel options for area employees, students, and residents (City of Boulder, 2022). However, it is not only a market opportunity for established players but also for new ones. The German start-up evcle in Munich, Germany, is an all-in-one mobility service provider that enables micromobility solutions for hotels, serviced apartments, residential neighborhoods, and municipalities (evhcle, 2022).

As shared micromobility services can contribute to a more sustainable future of mobility and seem to be a promising segment in the mobility market, understanding antecedents and possible outcomes of user adoption is an important task. For example, research proposes that the enhanced use of shared micromobility can contribute to several United Nations Sustainable Development Goals (SDGs; Chaudhuri et al., 2022; Lukasiewicz et al., 2022), including and well-being (SDG3) and sustainable communities (SDG 11). Nowadays, innovative technologies, products, and services, continue to emerge and evolve in our changing and demanding economic and social environment (Venkatesh et al., 2021). Accordingly, research on the adoption of new technologies, products, and services has highlighted the need to consider changing and dynamic importance of adoption factors over time (Blut et al., 2021), calling for the investigation of temporal issues in empirical adoption research (Venkatesh et al., 2021). This constant evolution in product and service design also applies to shared micromobility solutions (Lazarus et al., 2020), which are being described as a controversial and publicly debated topic (Bortoli, 2021; Gössling, 2020; Milakis et al., 2020). People may have already formed opinions without ever having used such a service. Consequently, users' perceptions will likely evolve as they gain user experience. Unfortunately, we still know little about why potential users adopt such micromobility solutions and how these perceptions might change over time. Previous literature on the adoption of shared micromobility is inadequate because it rarely considers closed-campus settings, is limited in examining antecedents and outcomes of initial intention to use, and does not examine longitudinal user experience effects.

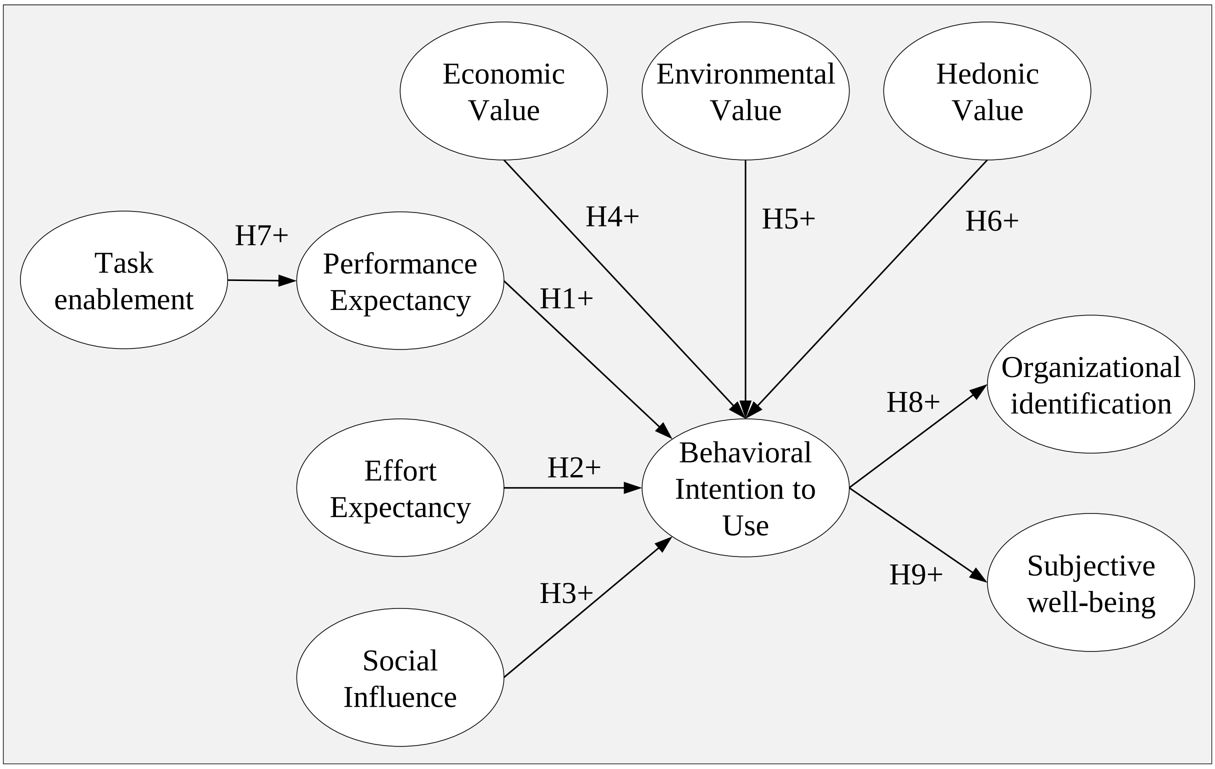
Against this background, this article analyzes the effects of user experience on the perception of antecedents and outcomes of adoption behavior of shared micromobility solutions in a closed campus environment. In cooperation with DHBW Drive, a field laboratory for micromobility at the Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany, we investigate how users' evaluations and perceptions evolve with testing and real usage experience. Therefore, we make the following theoretical contributions. First, we develop a longitudinal real user experience model to explain the antecedents and outcomes of closed campus micromobility adoption based on the unified theory of acceptance and use of technology (UTAUT2, Venkatesh et al. 2012). For this purpose, we extend the UTAUT2 by incorporating context-specific constructs from the theory of consumer perceived value (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), regulatory focus theory (Avnet & Higgins, 2006; Higgins, 1997) explaining next to the utilitarian path of technology adoption an affective promotion orientated path namely through subjective well-being, a key concept in transformative consumer research theories (Diener et al., 1999; Diener & Chan, 2011), and social identity theory (Ashforth & Mael, 1989). Second, by using a longitudinal within-subject study design, we integrate user experience effects and analyze the changing importance of predictors and outcomes over time, which is rare or even non-existent in the technology acceptance literature (Taylor & Todd, 1995; Venkatesh et al., 2002). Third, we operationalize and test the framework with empirical data coming from two independent user samples. The first study is based on an age- and gender-representative sample of inexperienced non-registered users (short-term experience), and the second study is a sample of registered DHBW Drive users (long-term experience). From a managerial perspective, the results will help inform operators and potential customers of micromobility solutions for closed campuses (e.g., universities, office and corporate campuses), and policymakers seeking to increase or manage the uptake of micromobility.

Our article is organized as follows. First, we provide a theoretical background about the antecedents and outcomes of behavioral intention to use a closed-campus micromobility service. Consequently, we formulate our hypotheses, followed by a description of the methodology and data. We then present and discuss the results. Finally, we highlight the implications for theory and practice, address the limitations of the research, and outline future research directions.

2 Theoretical Background and Hypotheses

Technology acceptance models and theories have been applied in a wide variety of fields to understand and predict user behavior. For our research, we choose the UTAUT2 (Venkatesh et al., 2012) since it is considered the most effective integrated model for analyzing new technology adoption at the end user level (Blut et al., 2021). In addition, the introduction of shared mobility services in the form of e-scooters has already been explained using UTAUT2 (e.g., Kopplin et al., 2021). We contribute to the literature on shared micromobility acceptance by adding new theories and associated variables to our model, which are explained below (see Figure 15).

Figure 15: Conceptual Model about Antecedents & Outcomes of Shared Micromobility



2.1.1 UTAUT2, Performance Expectancy and Effort Expectancy

Venkatesh et al. (2012) proposed the UTAUT2 as the most effective integrated model for analyzing technology acceptance and behavioral intention to use. In the UTAUT2 behavioral intention to use refers to the motivational factors that influence a given behavior (Venkatesh et al., 2003). Within the UTAUT2 model, according to regulatory theory (Higgins, 1997) utilitarian prevention-orientation core variables, performance expectancy and effort expectancy impact the behavioral intention to use new technologies (e.g., Venkatesh et al., 2012). Performance expectancy refers to "users' perceptions that using a new technology will improve their performance" (Venkatesh et al., 2003, p. 447) and effort expectancy refers to the "degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). Both variables are positively related to behavioral intentions to use a new technology (Venkatesh et al., 2012). Prevention-oriented benefits are important aspects in the adoption of new technologies, such as shared micromobility services, which are typically related to cognitive evaluation, product quality, rationality, decision effectiveness, goal orientation, convenience (e.g., effort and performance expectation), and drive individuals' behavioral intention to use the new technology. In the case of shared micromobility, previous research has highlighted that some of the most important perceived benefits are related to short-distance traveling, particularly for first- and last-mile trips in urban settings (Baek et al., 2021; Shaheen & Chan, 2016). Consequently, previous research about micromobility adoption has proven a positive relationship between performance expectancy on behavioral intention to use as well as between effort expectancy on behavioral intention to use (e.g., Kopplin et al., 2021; Rejali et al., 2021). Thus, we state the following hypothesis:

Hypothesis 1. Performance expectancy positively influences behavioral intention to use CCMM.

Hypothesis 2. Effort expectancy positively influences behavioral intention to use CCMM.

2.1.2 UTAUT2, Social Influence

Social cognitive theory shows that the adoption of new technologies is influenced by social learning and recognition (Bandura, 1989). Moreover, social cognitive theory embraces the motivations of social pressure for individuals who believe they should use a new technology to achieve higher social status or a more important position in the groups to which they belong (Bandura, 1989). The UTAUT2 draws on aspects of social cognitive theory by incorporating the variable of social influence, which is defined as the "degree to which individuals perceive that important others believe they should use the new system" (Venkatesh et al., 2003, p. 451). Thus, in the UTAUT2 an important motivation for individuals to adopt a new technology is the desire to gain social status as people generally want to be accepted by groups and therefore follow group norms (Cooper et al., 2001). Group norms are defined as the most common pattern of overt behavior for members of a given social system, which in turn impacts the intention to use a new technology (Cooper et al., 2001). The decision to adopt shared micromobility can be consistent with group norms to achieve group membership and identification (Sweeney & Soutar, 2001). In a meta-analysis on technology adoption models, Schepers and Wetzels (2007) highlight the overall influence of subjective norms and social influence on the behavioral intention to use a technology and as an important motivation for individuals to adopt new technologies. Shared micromobility is a new and innovative, but also discussed mode of urban transportation, and thus research has investigated and confirmed the importance of social influence on behavioral intention to use (e.g., e-scooter sharing; Eccarius & Lu, 2020; Kopplin et al., 2021, bike sharing; Gao et al., 2019). Therefore, we formulate our hypothesis:

Hypothesis 3. Social influence positively influences behavioral intention to use CCMM.

2.1.3 Consumer Perceived Value

Consumer perceived value is defined as "the overall assessment of the utility of a product based on perceptions of what is received and what is given" (Holbrook, 1994; Zeithaml, 1988, p. 14). A review of research about consumer perceived value theories in the context of micromobility services shows that micromobility provides several substantial benefits (Abduljabbar et al., 2021) that range, according to regulatory focus theory (Higgins, 1997), from utilitarian prevention orientated economic (e.g., saving time and money) as well as environmental benefits (e.g., more sustainable, environmentally friendly than a private vehicle), to promotion-orientated hedonic benefits (e.g., fun and relaxing).

Economic value refers to the consumers' perception when comparing the costs and benefits of using a product or service. When the benefits of perceived use outweigh the cost of money, the economic value is positive (Venkatesh et al., 2012). If the use of shared micromobility in an organizational, closed-campus setting shows a better cost-benefit ratio compared to previous or alternative transportation options, economic value has an important and positive effect on the behavioral intention to use such a service. Research has proven that economic value plays a significant role in the shared use of products and services (e.g., Lyu & Zhang, 2021). Therefore, we hypothesize the following:

Hypothesis 4. Perceived economic value positively influences behavioral intention to use CCMM.

Environmental value refers to the consumers' perception of whether using a service or product improves the environmental performance in their lives, and also includes an assessment of the sustainability and environmental friendliness of the used product (Flores & Jansson, 2021). As micromobility solutions are considered an essential component to reducing reliance on private vehicles and improving public health, studies have investigated that green perceptions were influential factors in explaining behavioral intentions to use micromobility (Chen, 2019; Huang et al., 2020; Liang et al., 2022). For example, Liang et al. (2022) show that perceived environmental value has a significant positive impact on re-using intention of bike sharing. Thus, we hypothesize:

Hypothesis 5. Perceived environmental value positively influences behavioral intention to use CCMM.

According to regulatory focus theory (Higgins, 1997), users have not only utilitarian prevention-orientation motivations (e.g., performance expectancy and effort expectancy) but also affective promotion-oriented motivations, such as hedonic value when choosing new technologies. Hedonic value refers to the users' overall judgments of experiential and emotional benefits of using a product or service (Babin et al., 1994) that are more subjective and personal than other factors and result more from consumer aesthetics, exploration, fun, and entertainment than from task completion (Meyer-Waarden & Cloarec, 2022). Some studies have investigated the positive influence of pleasure and hedonic value on behavioral intentions in the context of shared micromobility, showing that micromobility is perceived as entertaining and relaxing (Chen, 2016; Huang et al., 2020; Kopplin et al., 2021). For example, Chen (2016) highlight perceived hedonism as one of the key antecedents of using bike sharing services. Thus, we hypothesize the following:

Hypothesis 6. Perceived hedonic value positively influences behavioral intention to use CCMM.

2.1.4 Task Enablement

Task enablement is rooted in the theory of enabling employees to achieve their goals (Adler & Borys, 1996). Perceived enablement is defined as "the extent to which employees feel they are provided with what they need to do their jobs well and are provided with an environment in which they feel comfortable to perform to the best they can be" (Permana et al., 2015, p. 580). An enabling work environment is understood as one that provides the tools and processes to improve employee performance (Colenbaugh & Reigel, 2010). According to this definition, a shared micromobility service provided by an organization to its members can be understood as an enabling infrastructure tool to improve work and task performance. Research indicates that the use of e-scooters within a professional population is seen as a more convenient and faster way to get around a university campus than walking (Sanders et al., 2020). By providing a more convenient and faster mobility option for on-campus and off-campus travel, the service can both enable users to save time and effort on existing work and make possible workflows that may not have been possible in the past due to time and other constraints. This, in turn, should have a positive impact on users' perceptions of the performance expectations of closed-campus micromobility. Thus, we hypothesize:

Hypothesis 7. Task enablement positively influences performance expectancy of CCMM.

2.1.5 Organizational Identification

Organizational identification has its roots in social identity theory (Ashforth & Mael, 1989) and is defined as “the extent to which a person senses a oneness or sameness with the organization” (Korschun et al., 2014, p. 21). This identification is more than just a positive or negative evaluation of the organization, as it also involves a depersonalization of the self and the use of the organization as a means of self-definition and meeting self-defined needs (Homburg et al., 2009, p. 39). Organizational identification is considered an important factor in explaining individual attitudes and behaviors in organizations (Lee et al., 2015). Research has shown that organizational identification has a positive impact on the intention to remain loyal to an organization (Wan-Huggins et al., 1998) and that organizational support can promote organizational identification (Edwards & Peccei, 2010; Shen et al., 2014). Therefore, for closed-campus micromobility services, organizational identification may be important for at least two reasons: First, the provision of such a service can be understood by the users as an infrastructural, supporting (employer branding) tool, so that the use of the service improves the users’ identification with the organization. Second, strong organizational identification can lead to better use of the service (e.g., careful handling, and safe use). Thus, we hypothesize:

Hypothesis 8. Behavioral intention to use CCMM positively influences organizational identification.

2.1.6 Subjective Well-being

Subjective well-being has received increasing attention in transformative marketing research in recent years and has been studied in the fields of sociology, psychology, and even social media (Diener et al., 1999; Knight et al., 2009). It is defined as “a broad category of phenomena that includes people's emotional responses, domain satisfactions and global judgments of life satisfaction" (Diener et al., 1999, p. 277) and research has shown that subjective well-being is strongly affected by consumers' technology choices and usage (Diener & Chan, 2011). Micromobility services provide manifold and substantial benefits for users and for the environment that potentially improve user well-being. The relationship direction between technology acceptance behavior and perceived well-being is unclear in the literature, as the relationship can go either way. While on the one hand, perceived subjective well-being may affect adoption by reinforcing positive mental representations and feelings toward the technology, product, and service (Davis & Pechmann, 2013; Mick, 2012), shared micromobility adoption use might be an important predictor of perceived subjective well-being (Delbosc & Currie, 2011; Leyden et al., 2011; Woodcock et al., 2014). In this regard, the use of shared micromobility services can contribute to users' subjective well-being for the following reasons. First, the use of shared micromobility typically involves some form of outdoor physical activity, such as bike or e-scooter riding. Outdoor exercise has been shown to have a positive effect not only on physical health but also on mental health, reducing symptoms of depression and anxiety, among other things (Jones et al., 2016; Woodcock et al., 2014). For example, a study on the introduction of a bike sharing system in London showed that the average amount of physical activity per person per week increased and that there were noticeable health benefits at the population level (Woodcock et al., 2014). Second, shared micromobility can improve accessibility by providing more cost-effective transportation options to individuals who do not have access to a car or traditional public transportation (Mouratidis, 2021). This can improve users' sense of autonomy and financial stability, which in turn can lead to a greater sense of self-determination and empowerment, and thus happiness in life (Leyden et al., 2011). Transport disadvantage, on the other hand, that restricts access to all these options may hinder subjective well-being (Delbosc & Currie, 2011). Third, increased use of micromobility can contribute to a healthier environment by reducing greenhouse gas emissions and helping to reduce traffic congestion (Lindsay et al., 2011; Smith, 2017). For example, a study shows that private cars take up 15-30% of parking spaces in typical urban areas, while up to 20 e-scooters can be parked in the same space reserved for just one private car, offering the potential to improve well-being (VOI, 2019). In addition, studies have confirmed that traffic congestion and a longer commute can have significant negative effects on life satisfaction and subjective well-being (Clark et al., 2020; Sun et al., 2021). Therefore, the use of a more active, more accessible, more environmentally friendly, and enjoyable mode of transportation should improve the psychological and physical health of users and, consequently, their subjective well-being. Thus, we hypothesize:

> **Hypothesis 9.** Behavioral intention to use CCMM positively influences subjective user well-being.

3 Methodology

3.1 DHBW Drive – a Field Laboratory for Closed-campus Micromobility

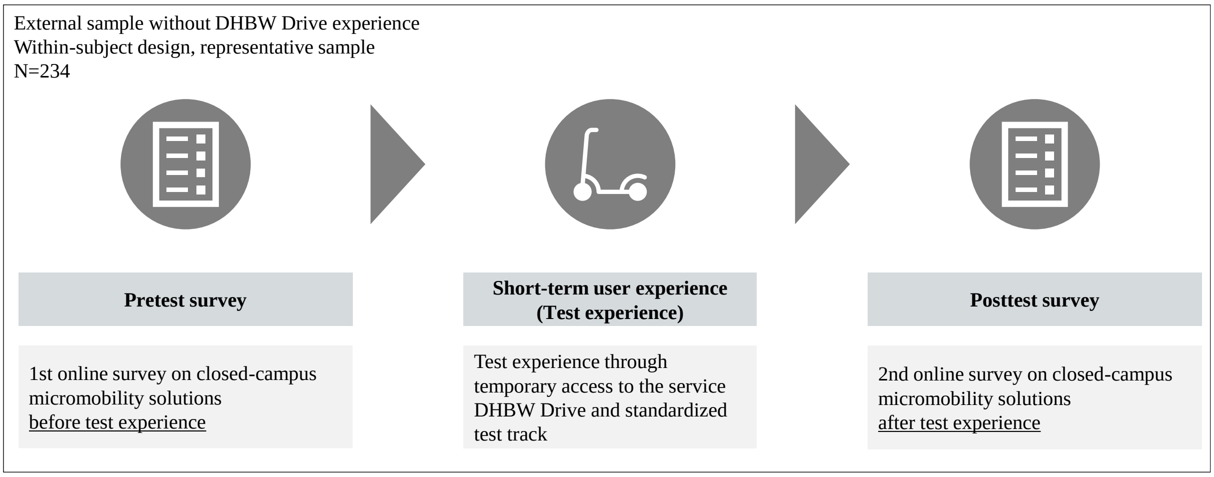
DHBW Drive was a field laboratory for shared closed-campus micromobility at Baden-Wuerttemberg Cooperative State University (DHBW) in Stuttgart, Germany, and represents the first successful micromobility sharing system in a closed-campus environment of a German university. With the service, members of the university (approx. 7,000 students and 400 staff) could move between 5 university sites in downtown Stuttgart. In total, a fleet of 70 e-scooters was free-of-charge available and could be rented and parked at defined stations via an app, customized for the field laboratory and available for Android and iOS smartphones. At the stations, the e-scooters were charged using an in-house developed charging concept. Over the duration of the operation, from October 2020 to February 2022, more than 2,200 persons were registered (with a share of 95% of students), more than 12,200 bookings were made, and a total of more than 38,600 km were traveled.

3.2 Research Design

We conducted two longitudinal studies with two independent test groups: Study 1 was a group of people who were non-registered users of the service DHBW Drive (external sample), and Study 2 was a group of people who were registered users of the service DHBW Drive (internal sample).

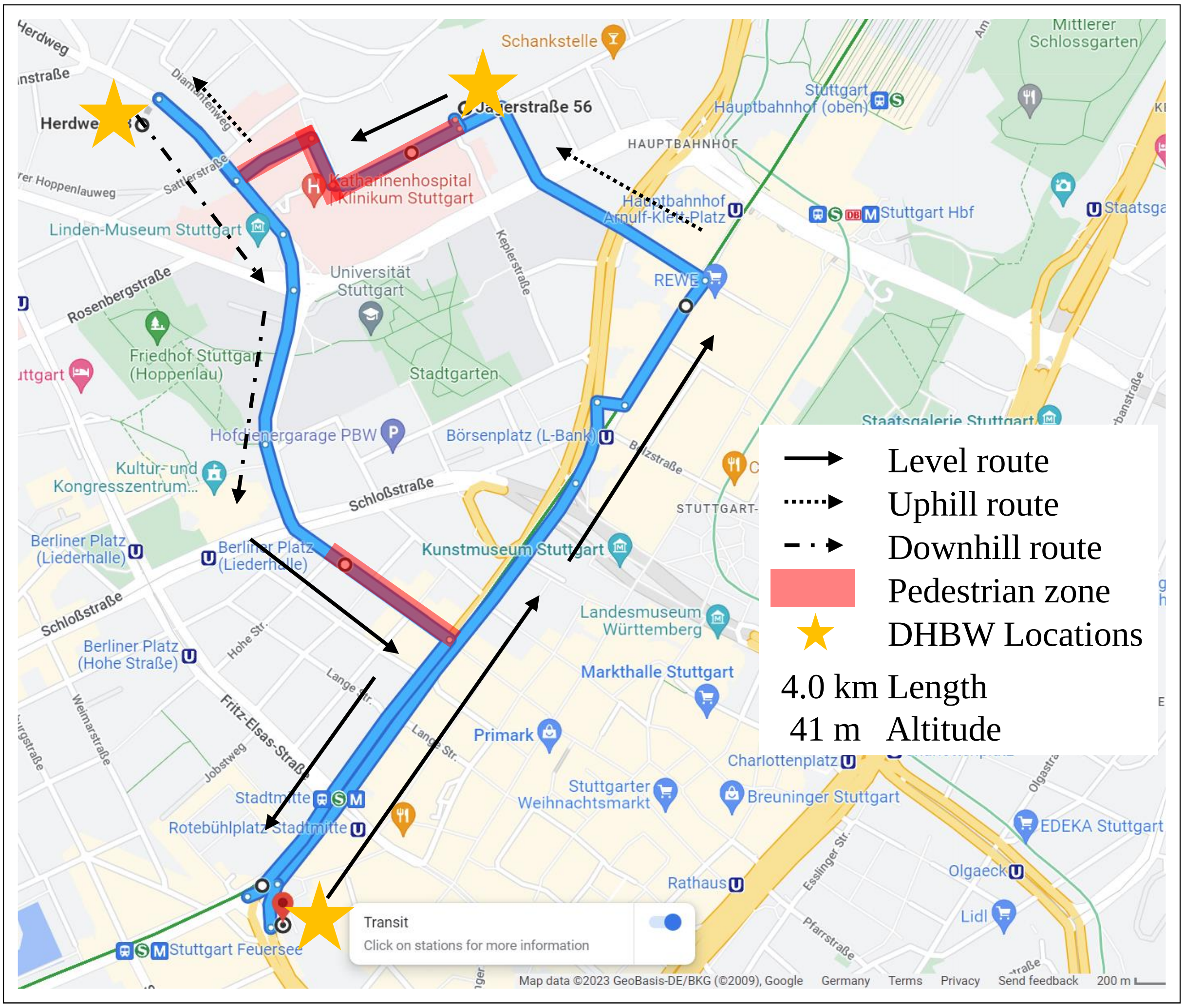
Study 1 had three parts: a pretest survey before the test experience, a standardized test experience, and a posttest survey after the test experience (see Figure 16).

Figure 16: Research Design Study 1 – External Sample



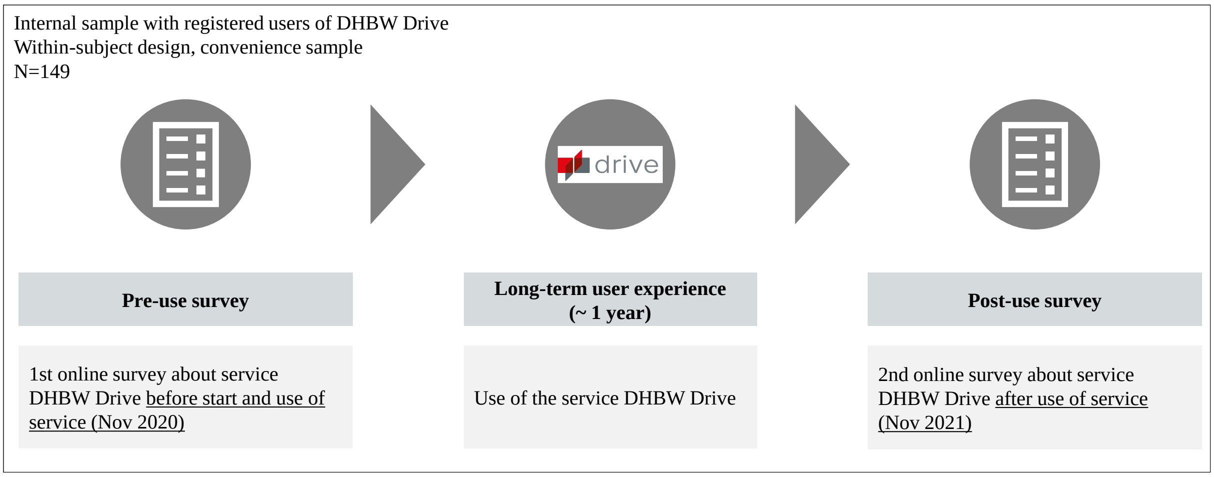
The pretest survey and the posttest survey were almost identical. The pretest survey included demographic questions, and the posttest survey included study feedback questions, in addition to the items related to variables in the conceptual model. After completing the pretest survey, the participants received an introduction to the service DHBW Drive and completed a guided test track to standardize the test experience. Since the use of micromobility vehicles in urban scenarios presents special challenges due to the complexity of the traffic and road environment and to simulate a closed-campus organizational situation, the test track was consciously designed and implemented. It was a round-trip crossing by three DHBW sites. Except for two pedestrian zones, where e-scooters were allowed to be used at walking speed, only designated bike lanes were used. The test track included uphill and downhill parts (41 meter changes in altitude), was 4.0 kilometers long, and lasted about 25 minutes in average traffic situations (see Figure 17). After temporary access, all respondents completed the posttest survey. Based on the within-subject design with non-registered users of DHBW Drive, we aimed to investigate how consumers' perceptions evolve before and after test experiences (short-term user experience) with the service DHBW Drive.

Figure 17: Standardized Test Track



Study 2 was conducted with members of Baden-Wuerttemberg Cooperative State University Stuttgart, who were registered users of DHBW Drive (internal sample). It was again implemented as a two-wave within-subject longitudinal study. Similar to Study 1, Study 2 consisted of three parts: the first survey at the beginning of the field laboratory (pre-use survey), long-term user experience, second survey after one year of field laboratory operation (post-use survey; see Figure 18).

Figure 18: Research Design Study 2 – Internal Sample



The pre-use survey and post-use survey were again nearly identical. In addition to the items related to the variables in the conceptual model, the pre-use survey included again demographic questions, and the post-use survey included questions to provide feedback on the operation of the field laboratory. The main difference between Study 1 (external sample) and Study 2 (internal sample) is that, compared to the testing experience in Study 1, the user experience in Study 2 covered a time span of about one year (long-term user experience) and was not standardized.

3.3 Study 1: External Sample (non-registered users of DHBW Drive)

To test and validate the conceptual model and investigate short-term changes, we first conducted a two-wave longitudinal study with external people, who did not know or use DHBW

Drive before and who were non-registered users. The study took place from 30/11/2021 to 23/12/2021. To have a representative sample of the German population, we implemented quotas according to the gender and age distribution of the Federal German Statistical Office updated in 2020 (Federal Statistical Office, 2020). In total, 265 persons without any DHBW Drive experience participated in the two-wave within-subject longitudinal study. Both surveys included one attention check in the form of a directed query (i.e., “I am not paying attention at all in this survey. Please tick ‘Do not agree at all’”) to detect inattentive respondents and increase statistical power (Abbey & Meloy, 2017). 31 respondents did not pass both attention checks, which is an acceptable loss of 11.7%. Finally, a total of data sets from 234 respondents were valid for statistical analysis. The gender distribution of our respondents was 44% females and 56% males. Furthermore, the median age was 36.5 years and the average age was 38.9 years. In terms of age and gender, our sample is well-distributed and representative of the German population. Regarding the previous experience with shared micromobility, 3.8% of the respondents were not aware of and did not use shared micromobility services before the test experience. 56.4% knew but did not use, 29.9% sporadically and 9.8% frequently used available shared micromobility services. As we investigate shared micromobility in closed-campus environments, we also asked for professional background. Regarding company size, the sample is again well-distributed. 7.3% were small companies with less than 10 employees; 22.8% were large companies with more than 5,000 employees. 76.9% of the respondents had an employee position, 15.0% a management position, 2.6% executive management position, and 3.9% managing partner position. Thus, good representativeness can be assumed in terms of the employment and professional background of the respondents (see Table 25).

Table 25: Study 1 – External Sample Description (non-registered users of DHBW Drive)

Variable	Value	Total	Relative [%]
Age	16 – 29	65	27.8
	30 – 39	58	24.8
	40 – 49	44	18.8
	50 – 59	54	23.1
	60 and older	13	4.7
Gender	Male	132	56.4
	Female	102	43.6
Prior experience with shared Micromobility	Not known and not used	9	3.8
	Known but not used	132	56.4
	Sporadically used	70	29.9
	Frequently used	23	9.8
Company size	Less than 10 employees	17	7.3
	11 – 50	35	15.1
	51 – 250	51	22.0
	251 – 1,000	46	19.8
	1,001 – 5,000	30	12.9
	More than 5,000 employees	53	22.8
Function	Employee position	180	76.9
	Management position	35	15.0
	Executive management position	6	2.6
	Managing partner position	9	3.9
Total		234	100

Note: The sum of the subtotals may not reach the 234 respondents due to missing values.

3.4 Study 2: Internal Sample (registered users of DHBW Drive)

To test and validate the conceptual model and investigate dynamic long-term changes, we conducted a two-wave within-subject longitudinal study with internal university members that were registered users of DHBW Drive. Both surveys in the study were distributed via an email list. The email list was provided by the DHBW Drive backend system. The first survey (pre-use survey) was sent six out weeks after the start of field laboratory operations (11/26/2020 to 12/20/2020). After one year of field lab operation, all respondents who participated in the first survey were asked to participate in the second post-use survey (11/23/2021 to 11/04/2021). In total, 158 registered users participated in both surveys. Both surveys included one attention check (i.e., "I am not paying attention at all in this survey; Please tick 'Fully disagree'") to detect inattentive respondents and increase statistical power (Abbey & Meloy, 2017). After the deletion of the inattentive respondents, 149 responses remained for statistical analysis. The gender distribution of our respondents was 79.2% females and 20.8% males (see Table 26). Furthermore, the average (median) age was 23.50 (20.00) years. Although our sample cannot be considered representative of the German population, the distribution of age and function are comparable to other German universities. In addition, it can be argued that samples from younger populations allow for comparisons and provide a prospective market for the adoption of new mobility technologies. This is because younger generations are typically more attracted to new technologies, goods, and services (Ashraf et al., 2014; Attie & Meyer-Waarden, 2023; Barbosa et al., 2019; Mcmillan & Morrison, 2006; Meyer-Waarden & Cloarec, 2022).

Table 26: Study 2 – Internal Sample Description (registered users of DHBW Drive)

Variable	**Value**	**Total**	**Relative [%]**
Age	18 – 29	131	87.9
	30 – 39	4	2.7
	40 – 49	5	3.4
	50 – 59	8	5.4
	60 and older	1	.7
Gender	Male	118	79.2
	Female	31	20.8
Function	Student	132	88.6
	Staff / Lecturer	17	12.4
Total		149	100

3.5 Measurement Instruments

All measurement scales were based on seven-point Likert scales ranging from (1 = fully disagree to 7 = fully agree) and adapted from previous studies. To compare the results of Study 1 and Study 2, we used the same scales and items in both studies. In Study 1 (external sample: non-registered users of DHBW Drive), we asked about the “potential use” of a closed campus micromobility service in general, and in Study 2 (internal sample: registered users of DHBW Drive), we asked about the “real use” of the service DHBW Drive specifically (Table 27).

To measure behavioral intention of use (e.g., “BI1: I intend to use the Service DHBW Drive in the future.; BI2: I will try to use the service DHBW Drive in my daily life.; BI3: I plan to make regular use of the service DHBW Drive.”), effort expectancy (e.g., “EE1: The use of the service DHBW Drive is effortless for me. EE2: My interaction with the service DHBW Drive is clear and understandable.; EE3: I find the service DHBW Drive easy to use.; EE4: Learning how to use the Service DHBW Drive is easy for me.”), performance expectancy (e.g., “PE1: I find the service DHBW Drive useful in my daily life.; PE2: Using the service DHBW Drive increases my chances of achieving important things.; PE3: Using the service DHBW Drive helps me get things done more quickly.; PE4: Using the service DHBW Drive increases my productivity.”), and social influence (e.g., “SI1: People who are important to me think that I should use the service DHBW Drive when making mobility decisions.; SI2: People who influence my behavior think that I should use the service DHBW Drive.; SI3: People whose opinions I value prefer that I use the service DHBW Drive.”), we adapted the scales from Venkatesh et al. (2012).

To measure utilitarian value (e.g., “UTT1: The service DHBW Drive makes it easier for me to reach my destinations.; UTT2: The service DHBW Drive makes my journeys convenient and more practical.; UTT3: The service DHBW Drive makes my journeys quicker.”), we adapted a scale from Meyer-Waarden (2013). To measure hedonic value (e.g., “HED1: Using the service DHBW Drive is fun.; HED2: Using the service DHBW Drive is enjoyable.; HED3: Using the service DHBW Drive is very entertaining."), we adapted the scale from Venkatesh et al. (2012). Economic value (e.g., "ECO1: I can save money by using the service DHBW Drive.; ECO2: Using the Service DHBW Drive can improve my economic situation.; ECO3: Using the service DHBW Drive benefits me financially.") and environmental value (e.g., "ENV1: The use of the service DHBW Drive is environmentally friendly.; ENV2: I feel that I am contributing to a sustainable environment by using the service DHBW Drive. ENV3: The service DHBW Drive is an example of a green service.") were both measured with a scale from Barnes and Mattsson (2017).

To measure task enablement (e.g., "ENA1: The service DHBW Drive enables me to better manage my work/studies, tasks and appointments (lectures, etc.).; ENA2: The service DHBW Drive helps me get from faster A to B.; ENA3: The service DHBW Drive helps me to better balance my work/studies with my leisure time.; ENA4: The service DHBW Drive enables me to work better with my colleagues/fellow students."), we adapted the scale of Permana et al. (2015).

Organizational identification (e.g., "OI1: I feel good about being a member of DHBW.; OI2: I like to tell other people that I am a member of DHBW.; OI3: The DHBW is a good fit for me.") was measured with a scale adapted from Homburg et al. (2009).

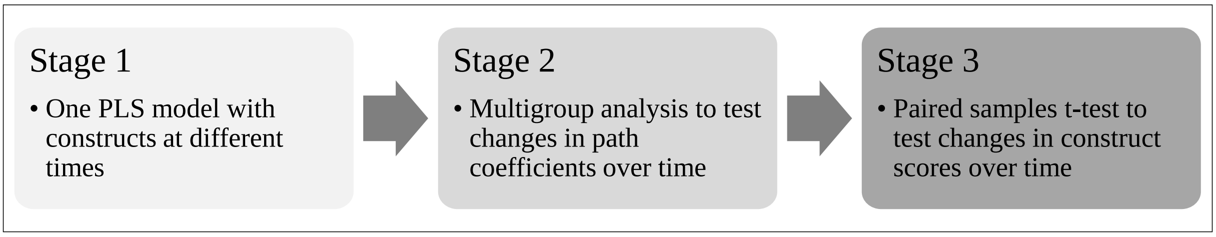
To measure subjective well-being (e.g., "SWB1: By using a closed-campus micromobility service, my quality of life would improve.; SWB2: By using a closed-campus micromobility service, my overall well-being would improve.; SWB3: By using a closed-campus micromobility service, I would feel happier."), we adapted a scale from Meyer-Waarden and Cloarec (2022).

We combined two approaches to minimize and assess common-method bias (CMB). First, we incorporated the CMB marker technique of Richardson et al. (2009) and separated the dependent variables (i.e., the behavioral intention of use, organizational identification, subjective well-being) spatially from the independent variables by inserting a theoretically irrelevant marker variable between the two areas of the questionnaire (see also Lindell & Whitney, 2001; Malhotra et al., 2006; Venkatesh et al., 2012). Second, CMB emerges when either a general factor is revealed by the data or a single factor accounts for the majority of the variation (Podsakoff et al., 2003). Accordingly, we applied Harman’s single-factor test in both data sets to assess for an emerging single factor. The single factor in Study 1 explained 35.6% of the total variance, and the single factor in Study 2 explained 35.8%. Since the recommended threshold of 50% was not exceeded, CMB is not an issue in both studies (Harman, 1976).

3.6 Evolution Model for Panel Data Approach in PLS-SEM

To analyze our conceptual model and examine longitudinal effects in a within-subjects design, we followed guidelines (Roemer, 2016) for analyzing longitudinal data using partial least squares structural equation modeling (PLS-SEM) and used the software SmartPLS 3.3.9 (Ringle et al., 2015). The “evolution model for panel data” is used when the same group of individuals has been surveyed repeatedly over time (Roemer, 2016) and suggests three stages of analysis. The first step is to test the significance and strength of path relationships by building a PLS model with constructs at different times. A multigroup analysis based on the nonparametric confidence set approach is the second stage to test for changes in the path coefficients over time (Sarstedt et al., 2011). The third step is the testing of changes in construct scores over time. Paired sample t-tests are used to do this (see Figure 19).

Figure 19: Evolution Model for Panel Data in PLS-SEM (adapted from Roemer, 2016)



Partial least squares (PLS-SEM) is used instead of covariance-based (CB-SEM) because PLS-SEM can handle more complex models and small sample sizes, and is more tolerant of the requirement for normally distributed data (Hair et al., 2019; Hulland, 1999; Richter et al., 2016), which all applies for our study. In addition, PLS-SEM is a widely accepted and increasingly used approach to SEM in the marketing research field (Hair et al., 2012; Henseler et al., 2009), and the number of published articles using PLS-SEM has increased significantly in recent years compared to CB-SEM (Hair et al., 2017).

A PLS-SEM model is usually analyzed and interpreted in two stages (Hulland, 1999). First, the measurement model is assessed for reliability and validity, and second, the structural model itself is evaluated. All constructs were specified as common factors and measured reflectively. The following specifications were used in running the PLS algorithm. The path weighting scheme was chosen as the structural model weighting scheme. The model was estimated with a maximum of 1,000 iterations (Hair et al., 2014). 10-7 was chosen as the stop criterion (Henseler et al., 2009). To test the significance and strength of the path coefficients, the bootstrapping procedure was run with 5,000 subsamples. The "no sign change" option was selected as the most conservative option (Hair et al., 2014).

3.6.1 Assessment of the Measurement Model

For both studies all latent constructs met the recommended Cronbach's, confirming reliability (Sarstedt et al., 2014, p. 108). The average variance extracted (AVE) clearly exceeded the minimum threshold of .5 for all constructs confirming convergent validity (see Table 27; Hair et al., 2019, p. 9). The Heterotrait-Monotrait (HTMT) ratio showed good scores for both studies confirming discriminant validity (Henseler et al., 2015), except for the relationship between task enablement (ENA) and performance expectancy (PE), which exceeded the recommended threshold of .85 (Hair et al., 2019, p. 9; Henseler et al., 2015). Therefore, we performed the statistical HTMT test (Henseler et al., 2015). Since the bias-corrected bootstrap confidence interval did not contain the value 1, a lack of discriminant validity could be excluded. Overall, the measurement model could thus be confirmed for both studies.

Table 27: Scales, Reliability (α), Convergent Validity (AVE), and Loadings

Constructs, sources, and items	**Study 1 – Pretest**	**Study 1 – Posttest**	**Study 2 – Pre-use**	**Study 2 – Post-use**
Economic value (Barnes & Mattsson, 2017)	α = .936 AVE = .886	α = .939 AVE = .892	α = .922 AVE = .865	α = .874 AVE = .874
ECO1: I could (can) save money by using a closed-campus micromobility service (the service DHBW Drive).	.938	.936	.907	.905
ECO2: Using a closed-campus micromobility service (the service DHBW Drive) could (can) improve my economic situation.	.937	.938	.924	.940
ECO3: Using a closed-campus micromobility service (the service DHBW Drive) service would benefit (benefits) me financially.	.949	.959	.958	.959
Hedonic value (Venkatesh et al., 2012)	α = .847 AVE = .767	α = .875 AVE = .801	α = .855 AVE = .774	α = .848 AVE = .764
HED1: Using a closed-campus micromobility service (the service DHBW Drive) would be (is) fun.	.921	.921	.886	.907
HED2: Using a closed-campus micromobility service (the service DHBW Drive) would be (is) enjoyable.	.893	.928	.925	.891

HED3: Using a closed-campus micromobility service (the service DHBW Drive) would be (is) very entertaining.	.809	.832	.825	.821
Environmental value (Barnes & Mattsson, 2017)	α = .893 AVE = .824	α = .935 AVE = .886	α = .895 AVE = .827	α = .923 AVE = .867
ENV1: The use of a closed-campus micromobility service (the service DHBW Drive) service would be (is) environmentally friendly.	.888	.928	.878	.935
ENV2: I would feel (feel) that I am contributing to a sustainable environment by using a closed-campus micromobility service (the service DHBW Drive)	.922	.949	.909	.925
ENV3: A closed-campus micromobility service (The service DHBW Drive) would be (is) an example of a green service.	.912	.947	.940	.933
Task enablement (Permana et al., 2015)	α = .851 AVE = .691	α = .887 AVE = .749	α = .874 AVE = .730	α = .834 AVE = .673
ENA1: A closed-campus micromobility service (The service DHBW Drive) could enable (can enable) me to better manage my work/studies, tasks and appointments (lectures, etc.).	.871	.925	.876	.857
ENA2: A closed-campus micromobility service (The service DHBW Drive) could help (can help) me get from faster A to B.	.811	.812	.738	.692
ENA3: A closed-campus micromobility service (The service DHBW Drive) could help (can help) me to better balance my work/studies with my leisure time.	.839	.854	.907	.891
ENA4: A closed-campus micromobility service (The service DHBW Drive) could enable (can enable) me to work better with my colleagues/fellow students.	.804	.867	.884	.828
Social influence (Venkatesh et al., 2012)	α = .714 AVE = .641	α = .841 AVE = .759	α = .822 AVE = .741	α = .803 AVE = .715

SI1: People who are important to me think that I should use a closed-campus micromobility service (the service DHBW Drive) when making mobility decisions.	.867	.908	.883	.864
SI2: People who influence my behavior think that I should use a closed-campus micromobility service (the service DHBW Drive).	.626	.781	.738	.753
SI3: People whose opinion that I value prefer that I use a closed-campus micromobility service (the service DHBW Drive).	.884	.919	.947	.912
Effort expectancy (Venkatesh et al., 2012)	α = .933 AVE = .832	α = .962 AVE = .898	α = .912 AVE = .792	α = .903 AVE = .774
EE1: The use of a closed-campus micromobility service (the service DHBW Drive) would be (is) effortless for me.	.895	.950	.882	.840
EE2: My interaction with a closed-campus micromobility service (the service DHBW Drive) would be (is) clear and understandable.	.927	.962	.921	.911
EE3: I find a closed-campus micromobility service (the service DHBW Drive) easy to use.	.904	.918	.911	.932
EE4: Learning how to use a closed-campus micromobility service (the service DHBW Drive) would be (is) easy for me.	.922	.960	.843	.831
Performance expectancy (Venkatesh et al., 2012)	α = .901 AVE = .772	α = .898 AVE = .765	α = .890 AVE = .752	α = .876 AVE = .730
PE1: I would find (find) a closed-campus micromobility service (the service DHBW Drive) useful in my daily life.	.830	.881	.852	.797
PE2: Using a closed-campus micromobility service (the service DHBW Drive) would increase (increases) my chances of achieving important things.	.895	.860	.867	.834
PE3: Using a closed-campus micromobility service (the service DHBW Drive) would help (helps) me get things done more quickly.	.909	.888	.879	.883

PE4: Using a closed-campus micromobility service (the service DHBW Drive) would increase (increases) my productivity.	.879	.869	.871	.899
Behavioral intention of use (Venkatesh et al., 2012)	α = .893 AVE = .824	α = .929 AVE = .875	α = .870 AVE = .794	α = .871 AVE = .796
BI1: I would intend (intend) to use a closed-campus micromobility service (the service DHBW Drive) service in the future.	.883	.918	.853	.836
BI2: I would try (will try) to use a closed-campus micromobility service (the service DHBW Drive) in my daily life.	.919	.937	.895	.911
BI3: I would plan (plan) to make regular use of a closed-campus micromobility service (the service DHBW Drive).	.921	.951	.925	.927
Organizational identification (Homburg et al., 2009)	α = .851 AVE = .771	α = .902 AVE = .837	α = .901 AVE = .835	α = .901 AVE = .834
OI1: I would feel (feel) good about being a member of the providing organization (DHBW).	.897	.933	.925	.927
OI2: I would like (like) to tell other people that I am a member of the providing organization (DHBW).	.835	.873	.900	.920
OI3: The providing organization (The DHBW) would be (is) a good fit for me.	.901	.937	.916	.893
Subjective well-being (Meyer-Waarden & Cloarec, 2022)	α = .915 AVE = .854	α = .944 AVE = .899		
SWB1: By using a closed-campus micromobility service (the service DHBW Drive), my quality of life would improve (improves).	.925	.925		
SWB2: By using a closed-campus micromobility service (the service DHBW Drive), my general well-being would improve (improves).	.920	.920		
SWB3: By using a closed-campus micromobility service (the service DHBW Drive), I would feel (feel) happier.	.928	.928		

3.6.2 Assessment of the Structural Model

The modeling approach of PLS-SEM is fundamentally different from CB-SEM because the algorithm for obtaining PLS-SEM solutions is not based on minimizing the divergence between the observed and estimated covariance matrices (Hair et al., 2019). Goodness-of-fit measures of CB-SEM, which use the concept of chi-square-based model fit measures, cannot be applied to PLS-SEM (Hair et al., 2019; Hulland, 1999). Therefore, the criteria used for PLS-SEM models, path coefficients, and p-values, were used for the evaluation of the quality of the structural model. The internal variance inflation factors (VIFs) for both models were significantly less than 5.0, indicating that there were no problems concerning multicollinearity.

4 Results

The results of the evolution model for the panel data approach in PLS-SEM (Roemer, 2016) are illustrated and described below for Study 1 (external sample: non-registered users of DHBW Drive) and Study 2 (internal sample: registered users of DHBW Drive).

4.1 Results Study 1: External Sample (non-registered users of DHBW Drive)

In the first stage of the evolutionary model of the panel data approach, a single PLS model with constructs at different points in time (before and after the test of the service DHBW Drive) was developed for both studies to test the significance and strength of the path relationships at different times (Roemer, 2016). Table 28 illustrates the results of Study 1. Performance expectancy has a positive and significant effect on behavioral intention to use for both times, before and after the test of DHBW Drive ($\beta_{Pretest} = .321$, $p_{Pretest} < .001$; $\beta_{Posttest} = .305$, $p_{Posttest} < .001$). Thus, H1 is fully supported. Effort expectancy shows no significant impact on behavioral intention before and after the test of DHBW Drive ($\beta_{Pretest} = .100$, $p_{Pretest} > .05$; $\beta_{Posttest} = .004$, $p_{Posttest} > .05$). Thus, H2 is fully rejected. Social influence shows no significant impact on behavioral intention before and after the test of DHBW Drive ($\beta_{Pretest}$ = .032, $p_{Pretest}$ > .05; $\beta_{Posttest}$ = -.038, $p_{Posttest}$ > .05). Thus, H3 is also fully rejected. Economic value has no positive and significant effect on behavioral intention to use before and after the test of DHBW Drive ($\beta_{Pretest}$ = .065, $p_{Pretest}$ > .05; $\beta_{Posttest}$ = -.012, $p_{Posttest}$ > .05). So, H4 is fully rejected. However, environmental value has a positive and significant effect on behavioral intention to use before and after the test of DHBW Drive ($\beta_{Pretest}$ = .174, $p_{Pretest}$ < .001; $\beta_{Posttest}$ = .169, $p_{Posttest}$ < .001). Therefore, H5 is fully supported. Hedonic value has a positive and significant effect on behavioral intention to use before and after the test of DHBW Drive ($\beta_{Pretest}$ = .336, $p_{Pretest}$ < .001; $\beta_{Posttest}$ = .307, $p_{Posttest}$ < .001). Therefore, H6 is fully supported. Task enablement has a positive and significant effect on performance expectancy before and after the test of DHBW Drive ($\beta_{Pretest}$ = .880, $p_{Pretest}$ < .001; $\beta_{Posttest}$ = .616, $p_{Posttest}$ < .001). Thus, H7 is fully supported. Behavioral intention has a positive and significant effect on organizational identification before the test of DHBW Drive ($\beta_{Pretest}$ = .130, $p_{Pretest}$ < .05) but does not show a significant effect after the test of DHBW Drive ($\beta_{Posttest}$ = .059, $p_{Posttest}$ > .05). Thus, H8 is partly supported. Finally, behavioral intention has a positive and significant effect on subjective well-being before and after the test of DHBW Drive ($\beta_{Pretest}$ = .533, $p_{Pretest}$ < .001; $\beta_{Posttest}$ = .404, $p_{Posttest}$ < .001). Thus, H9 is fully supported.

Table 28: Study 1 – Stage 1 Results PLS-SEM

	Model Pretest			**Model Posttest**			
Relationship	**Path coefficient**	**p value**	**Sig.**	**Path coefficient**	**p value**	**Sig.**	**Result**
H1. PE → BI	.321	.000	***	.305	.000	***	Fully supported
H2. EE → BI	.100	.123	ns	.004	.937	ns	Fully rejected
H3. SI → BI	.032	.546	ns	-.038	.523	ns	Fully rejected
H4. ECO → BI	.065	.329	ns	-.012	.820	ns	Fully rejected
H5. ENV → BI	.174	.000	***	.169	.000	***	Fully supported
H6. HED → BI	.336	.000	***	.307	.000	***	Fully supported
H7. ENA → PE	.820	.000	***	.616	.000	***	Fully supported
H8. BI → OI	.130	.038	*	.059	.086	ns	Partly supported

H9. BI → SWB	.533	.000	***	.404	.000	***	Fully supported

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification; SWB = Subjective Well-being
* p < .05; ** p < .01; *** p < .001; ns p > .05

In the second step of the evolutional model of panel data approach (Roemer, 2016) a test was performed to check whether the changes in the path coefficients before and after the DHBW Drive test experience are significant. For this purpose, we used a nonparametric confidence set approach (Sarstedt et al., 2011). There is no significant difference between the path coefficients if the path coefficient for the pretest model falls within the confidence interval of the path coefficient for the posttest model. Conversely, there is a significant difference between the path coefficients if the path coefficient for the pretest model falls outside the confidence interval of the path coefficient for the posttest model. Table 29 summarizes the results of the non-parametric confidence set approach. Overall, a decrease in path coefficients can be observed from before to after the test experience of DHBW Drive, except for the relationship between performance expectancy and behavioral intention. However, only the decreases in the relationships of task enablement on performance expectancy ($\beta_{\text{Posttest-Pretest}}$ = -.204), behavioral intention on subjective well-being ($\beta_{\text{Posttest-Pretest}}$ = -.129), and behavioral intention on organizational identification ($\beta_{\text{Posttest-Pretest}}$ = -.071) are significant.

Table 29: Study 1 – Stage 2 Path Changes before/after use experience

	Model Pretest		**Model Posttest**			
Relationship	**Path coefficient**	**Bias corrected CI**	**Path coefficient**	**Bias corrected CI**	**Path difference**	**Sig.**
H1. PE → BI	.321	[.180; .456]	.305	[.162; .445]	-.016	No
H2. EE → BI	.100	[-.025; .230]	.004	[-.099; .111]	-.096	No
H3. SI → BI	.032	[-.074; .131]	-.038	[-.155; .074]	-.070	No
H4. ECO → BI	.065	[-.06; .201]	-.012	[-.117; .096]	-.077	No

H5. ENV → BI	.174	[.079; .276]	.169	[.072; .261]	-.005	No
H6. HED → BI	.336	[.189; .469]	.307	[.194; .423]	-.029	No
H7. ENA → PE	.820	[.765; .863]	.616	[.484; .732]	-.204	Yes
H8. BI → OI	.130	[.011; .256]	.059	[-.007; .126]	-.071	Yes
H9. BI → SWB	.533	[.427; .616]	.404	[.291; .503]	-.129	Yes

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification; SWB = Subjective Well-being

In the third and last step of the evolutional model of panel data approach (Roemer, 2016) we tested for changes in construct scores over time, by using paired samples t-tests (see Table 30). As a parametric procedure, the paired sample t-test makes a number of assumptions, e.g., that the difference between the paired values is normally distributed. We checked for normal distribution with the Shapiro-Wilk normality test and, if the test indicated a violation of the normal distribution assumption, we instead used the nonparametric Wilcoxon signed-ranks test alternative. Using this procedure, three significant changes in constructs over time can be detected: After the test experience of the service DHBW Drive, effort expectancy, hedonic value, and behavioral intention score significantly higher than before testing.

Table 30: Study 1 – Stage 3 Construct Changes before/after use experience

Constructs	**Mean Pretest**	**Mean Posttest**	**Mean difference**	**Statistic**	**p value**	**Effect size**
PE	3.69	3.75	.059	Wilcoxon W	.254	-
EE	5.71	5.86	.149	Wilcoxon W	.011*	.220
SI	4.04	3.93	-.109	Student’s t	.150	-
HED	5.25	5.50	.255	Wilcoxon W	0 .000***	.339
ECO	3.59	3.49	-.095	Wilcoxon W	.502	-
ENV	4.85	4.81	-.043	Wilcoxon W	.592	-
ENA	3.44	3.55	.110	Wilcoxon W	.062	-
BI	4.76	4.88	.112	Wilcoxon W	.040*	.167
OI	5.72	5.62	-.102	Wilcoxon W	.053	-
SWB	3.61	3.56	-.044	Wilcoxon W	.862	-

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence;
HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification;
SWB = Subjective Well-being
* p < .05; ** p < .01; *** p < .001

4.2 .Results Study 2: Internal Sample (registered users of DHBW Drive)

We used the same methodological approach as in Study 1 to test our model with the sample from Study 2 (internal sample: registered users of DHBW Drive). In the first stage of the evolutionary model of the panel data approach (Roemer, 2016), a single PLS model with constructs at different points in time (before and after one year of using the service DHBW Drive) was developed to test the significance and strength of the path relationships at different times (see Table 31). Performance expectancy has a positive and significant effect on behavioral intention to use before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .363, $p_{Pre\text{-}use}$ < .001; $\beta_{Post\text{-}use}$ = .451, $p_{Post\text{-}use}$ < .001). Thus, H1 is fully supported. Effort expectancy shows no significant impact on behavioral intention before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .036, $p_{Pre\text{-}use}$ > .05; $\beta_{Post\text{-}use}$ = -.006, $p_{Post\text{-}use}$ > .05). Thus, H2 is fully rejected. Social influence shows no significant impact on behavioral intention before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = -.028, $p_{Pre\text{-}use}$ > .05; $\beta_{Post\text{-}use}$ = .015, $p_{Post\text{-}use}$ > .05). Thus, H3 is also fully rejected. Economic value has a positive and significant effect on behavioral intention before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .223, $p_{Pre\text{-}use}$ < .01; $\beta_{Post\text{-}use}$ = .242, $p_{Post\text{-}use}$ < .01). So, H3 is fully supported. However, environmental value has no positive and significant effect on behavioral intention to use before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .176, $p_{Pre\text{-}use}$ > .05; $\beta_{Post\text{-}use}$ = .005, $p_{Post\text{-}use}$ > .05). Therefore, H5 is fully rejected. Hedonic value has a positive and significant effect on behavioral intention to use before DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .226, $p_{Pre\text{-}use}$ < .05), however, no effect can be detected after

DHBW Drive use ($\beta_{Post\text{-}use}$ = .039, $p_{Post\text{-}use}$ > .05). Therefore, H6 is only partly supported. Task enablement has a positive and significant effect on performance expectancy before and after DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .786, $p_{Pre\text{-}use}$ < .001; $\beta_{Post\text{-}use}$ = .708, $p_{Post\text{-}use}$ < .001). Thus, H7 is fully supported. Finally, behavioral intention has a positive and significant effect on organizational identification before DHBW Drive use experience ($\beta_{Pre\text{-}use}$ = .268, $p_{Pre\text{-}use}$ < .01) but has no significant effect after DHBW Drive use ($\beta_{Post\text{-}use}$ = -.036, $p_{Post\text{-}use}$ > .05). Thus, H8 is only partly supported. The relationship between behavioral intention and subjective well-being could not be examined in Study 2 because the construct of subjective well-being was not included in the two-wave longitudinal survey of Study 2.

Table 31: Study 2 – Stage 1 Results PLS-SEM

	Model Pre-use			**Model Post-use**			
Relationship	**Path coefficient**	**p value**	**Sig.**	**Path coefficient**	**p value**	**Sig.**	**Result**
H1. PE → BI	.363	.000	***	.451	.000	***	Fully supported
H2. EE → BI	.036	.629	ns	-.006	.926	ns	Fully rejected
H3. SI → BI	-.028	.747	ns	.015	.823	ns	Fully rejected
H4. ECO → BI	.223	.009	**	.242	.001	**	Fully supported
H5. ENV → BI	.076	.378	ns	.005	.925	ns	Fully rejected
H6. HED → BI	.226	.023	*	.039	.484	ns	Partly supported
H7. ENA → PE	.786	.000	***	.708	.000	***	Fully supported
H8. BI → OI	.268	.001	**	-.036	.537	ns	Partly supported
H9. BI → SWB	-	-	-	-	-	-	-

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification; SWB = Subjective Well-being
* p < .05; ** p < .01; *** p < .001, ns p > .05

In the second step of the evolutional model of panel data approach (Roemer, 2016) a test was performed to check whether the changes in the path coefficients before and after the DHBW Drive use experience are significant (see Table 32). Only two path changes are significant: the impact of hedonic value on behavioral intention ($\beta_{\text{Post-use-Pre-use}}$ = -.187) and the impact of behavioral intention on organizational identification ($\beta_{\text{Post-use-Pre-use}}$ = -.304) both decrease significantly.

Table 32: Study 2 – Stage 2 Path Changes before/after use experience

Relationship	Model Pretest		Model Posttest		Path difference	Sig.
	Path coefficient	**Bias corrected CI**	**Path coefficient**	**Bias corrected CI**		
H1. PE → BI	.363	[.195; .538]	.451	[.307; .592]	.088	No
H2. EE → BI	.101	[.007; .205]	.029	[-.055; .113]	-.072	No
H3. SI → BI	-.028	[-.199; .137]	.015	[-.122; .142]	.043	No
H4. ECO → BI	.223	[.053; .386]	.242	[.100; .380]	.019	No
H5. ENV → BI	.076	[-.089; .246]	.005	[-.105; .122]	-.071	No
H6. HED → BI	.226	[.034; .423]	.039	[-.073; .144]	-.187	Yes
H7. ENA → PE	.786	[.712; .844]	.708	[.602; .792]	-.078	No
H8. BI → OI	.268	[.117; .419]	-.036	[-.151; .077]	-.304	Yes
H9. BI → SWB	-	-	-	-	-	-

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification; SWB = Subjective Well-being

In the third and last step of the evolutional model of panel data approach (Roemer, 2016) we tested for changes in construct scores over time, by using paired samples t-tests. Whenever the normal distribution of mean differences assumption was not applicable, we relied on the nonparametric Wilcoxon signed-ranks test alternative. We find four significant changes in the constructs. They are all negative (see Table 33). Approximately one year after using the service DHBW Drive, performance expectancy, task enablement, behavioral intention, and organizational identification were significantly lower evaluated than before.

Table 33: Study 2 – Stage 3 Construct Changes before/after use experience

Constructs	Mean Pretest	Mean Posttest	Mean difference	Statistic	p value	Effect size
PE	5.25	4.95	-.306	Student's t	.005**	.232
EE	6.34	6.28	-.052	Wilcoxon W	.682	-
SI	4.18	4.08	-.094	Student's t	.415	-
HED	6.49	6.55	.061	Wilcoxon W	.274	-
ECO	4.38	4.61	.229	Student's t	.061	-
ENV	4.94	4.79	-.145	Student's t	.090	-
ENA	5.21	4.93	-.279	Wilcoxon W	.003**	.290
BI	6.04	5.68	-.361	Wilcoxon W	.000***	.442
OI	5.80	5.32	-.473	Wilcoxon W	.000***	.481
SWB						

Note: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; HED = Hedonic Value; ECO = Economic Value; ENV = Environmental Value; ENA = Task Enablement; BI = Behavioral Intention to Use; OI = Organizational Identification; SWB = Subjective Well-being
* p < .05; ** p < .01; *** p < .001

5 Discussion of the Results

Our results are mostly in line with previous findings about the adoption of shared mobility options. We confirm regulatory focus theory (Avnet & Higgins, 2006; Higgins, 1997), which argues that there are two types of goals when making decisions to adopt micromobility service technologies: utilitarian, prevention-oriented goals (e.g., performance through enablement in daily tasks and duties), and affective, promotion-oriented goals (e.g., enjoyment, sustainability). We furthermore highlight that people who have higher intention to use did also experience higher levels of subjective well-being. This relationship remains stable after test experience. Finally, we show that the provision of a shared micromobility service in an organizational setting can strengthen the bonds between an organization and its members. People having higher intentions to use also show higher identification with the providing organization. However, we also detect differing findings and new insights, which will be discussed subsequently.

First, in line with the UTAUT2 literature (Venkatesh et al., 2012), our research shows in both studies (external non-registered and internal registered DHBW Drive users) and for both measurement times (before and after DHBW Drive test or use experience) the positive direct effect between performance expectancy and the behavioral intention to use shared micromobility services (Venkatesh et al., 2012). Users are more likely to use the shared micromobility service if they perceive it as performing well, which is consistent with previous research (e.g., Kopplin et al., 2021). Specifically in the context of closed-campus systems, which are mostly used in professional, work-related, and task-oriented settings, we show that assessing performance is highly related to daily work and tasks. For both studies and measurement times, task enablement (e.g., the extent to which people believe they are provided with an enabling infrastructure in which they feel comfortable performing at their best) emerges as a significant antecedent of performance expectancy (Permana et al., 2015). As a result, the more the service is perceived as an enabling mobility tool, the more it will be viewed as a performance enhancer and the more likely it will be adopted. Taking longitudinal user experience effects into account, both relationships (e.g., performance expectancy on behavioral intention, task enablement on performance expectancy) remain stable in both studies, as there are no significant changes in the path coefficients. However, there is a significant decrease in the performance expectancy scores after using DHBW Drive for the internal sample of registered users (and not for the external sample). Therefore, it can be concluded that performance expectancy and task enablement are stable predictors of the intention to use closed-campus micromobility solutions.

Second, and in contrast to the UTAUT2 literature (Venkatesh et al., 2012), we do not support existing research about the positive link between effort expectancy and behavioral intention to use. This may be explained by the fact that, compared to other technological products or services, the expectation of effort for micromobility services, expressed in terms of ease of use, is less important for the evaluation of behavioral intention. This is because most people feel that they can easily book and use a bicycle or e-scooter (Ma et al., 2019). In fact, people are becoming more comfortable using app-based mobility services as the use of information technology rapidly advances and becomes more convenient (Peng et al., 2019). Consequently, effort expectancy expressed as ease of use of online-based service is becoming less important in the usage decision process. Beyond what is specific to our context, people in professional settings typically have high levels of self-efficacy and belief that they can successfully use new technologies despite the effort required to learn and master them (Skoumpopoulou et al., 2018).

Next, and again in contrast to UTAUT2 literature (Venkatesh et al., 2012), we do not find that social influence positively impacts the behavioral intention to use in either of the studies and at either of the assessment times (before and after user experience). Previous research on micromobility, which also found no significant effect of social influence on intention to use bike-sharing systems, provides possible explanations (Gao et al., 2019). Users choose to share micromobility instead of driving, taking the bus, or walking, and it appears that most of them are not influenced by other individuals when they choose their individual mode of transportation. In addition, shared micromobility is a controversially debated topic, with both proponents and opponents of such services (Gössling, 2020), which explains the lack of effect of the social environment (Bandura, 1989).

Third, our research confirms that micromobility services are perceived manifold in terms of consumer value. In line with existing research, hedonic value strongly positively influences the behavioral intention to use before the experience of DHBW Drive in both studies (Chen, 2016; Kopplin et al., 2021). In Study 2, however, the influence of hedonic value on intention to use decreases and becomes insignificant after experiencing the service, although the rating of hedonic values on the Likert scale remains stable and does not decrease significantly. A possible explanation for this could be habituation effects (Ajzen, 2002; Griffin et al., 2000). The process of habituation changes the reference points of individual responses within a given situation and alters the perceived value of everyday events, as consumers become accustomed to their environment and their expectations are aligned with it (Griffin et al., 2000). Consequently, the perceived hedonic value of using the micromobility is stronger before experience with the service, but then decreases with increasing user experience, as a habituation effect sets in. A practical explanation could be that after a long-term user experience, DHBW Drive users still perceive the service as entertaining, but this evaluation does not necessarily implicate a high intention to use the service. Another reason could be that micromobility is usually associated with leisure activities that have a high hedonic value (Christoforou et al., 2021; Gebhardt et al., 2021; Lang et al., 2022). Thus, if DHBW Drive users, after experiencing the service, do not see any concrete applications for their everyday study or professional life, the evaluation does not necessarily contribute to a higher usage intention.

Fourth, with regard to the environmental value, our results do not give a clear conclusion. For non-registered external users (Study 1), the path coefficients and construct ratings do not change after the test experience, indicating that environmental value has a stable positive effect on usage intentions. These users think that using micromobility in closed-campus systems improves their environmental footprint and contributes to sustainable mobility behavior, which has a positive impact on their intention to use micromobility solutions (Chen, 2019; Huang, 2020; Liang et al., 2022). For registered internal users (Study 2), the results are attenuated. The effect of environmental value on behavioral intention to use is not significant before and after using the service, with no change in path coefficients and construct scores over time. One explanation could be found in the individual setting of the service DHBW Drive. Most of the registered internal users in Study 2 are young people and students at DHBW University. Students already tend to travel more sustainably than older people (Abouelela et al., 2021; Chen et al., 2021; Flores & Jansson, 2021) and often live in urban areas, close to university or work, and therefore have short commutes. They tend to use public transport and private bicycles instead of cars, and they rarely use motorized private transport, considering that they already have a low environmental footprint. Therefore, the environmental value may no longer be a relevant factor to them (Flores & Jansson, 2021).

Fifth, with regard to the economic value, our results do not give a clear conclusion. For registered internal users (Study 2), economic value has a positive effect on behavioral intention to use before and after use of the service, whereas the effects are not significant for both measurement times for non-registered external users (Study 1). Moreover, the mean scores indicate that registered internal DHBW Drive users perceive higher economic value (compared to previous or alternative transportation options) than non-registered external users. One explanation for this could again be found in the samples. Students usually have no or only a low disposable income and even a small savings potential due to the DHBW Drive can significantly improve their financial situation and thus explain their higher intentions to use (Oeschger et al., 2020). Compared to the student context (Study 2), the external sample in Study 1 (non-registered users who would use micromobility in a professional and organizational setting) tend to pay less or no attention to the monetary costs of use (Venkatesh et al., 2012).

Sixth, subjective well-being is a consequence of the behavioral intention to use closed-campus micromobility services. For non-registered external users (Study 1), we detect a strong positive relationship between intention to use closed-campus micromobility service on subjective well-being before and after use experience. By using the service, these users also report higher subjective well-being. We do not find this relationship for the registered internal users (Study 2), as this construct was not included in the survey of the two-wave longitudinal study. However, the empirical confirmation of the positive relationship in Study 1 is particularly interesting as in most adoption studies, subjective well-being is considered as an antecedent and not as an outcome of usage intention. Our tested model is in line with research about shared micromobility stating that micromobility use can help to maintain personal mobility, reduce the negative environmental impact of mobility behavior, and consequently promote health and well-being (Jones et al., 2016; Lindsay et al., 2011; Woodcock et al., 2014).

Seventh, we confirm the positive impact of behavioral intention to use shared micromobility on organizational identification as an outcome. Thus, the hypothesis that providing a closed-campus micromobility solution to the members of an organization enhances their identification with the organization, can be partly supported. For both studies, non-registered external users (Study 1) and registered internal users (Study 2), we confirm the positive significant relationship before the use of the service DHBW Drive. However, in both studies, the path coefficients significantly decrease and become non-significant after the experience with service. In addition, construct scores are significantly lower after use for registered internal users (Study 2). A possible explanation could be again found in habituation effects (Ajzen, 2002; Griffin et al., 2000) because consumers become habituated to their environment and, accordingly, tend to value things that are not available but are desirable at a higher rate (Griffin et al., 2000). Conversely, people quickly get used to things, take them for granted, and often value them less with increasing use. As in both models, the relationship is positive in the first survey, we still believe that our theoretical considerations were aimed. The fact that students are only temporarily tied to a university could also explain why organizational identification decreases for the registered internal users (Study 2). This, in turn, may lead students to change their orientation toward graduation, so that the provision of organizational services no longer influences their identification with the university.

Finally, and based on a comparison of construct scores over time, we show that inexperienced people (Study 1, non-registered users of DHBW Drive) express a significantly higher level of intention to use the closed-campus micromobility service after the short-term experience with the service DHBW Drive. However, we find opposite results for the long-term experience. After one year of using the service DHBW Drive (long-term user experience), registered users of DHBW Drive (Study 2) report a significantly lower behavioral intention to use the service DHBW Drive.

6 Contributions

6.1 Theoretical Contributions

Shared micromobility services will impact urban development by providing a more flexible and sustainable means of transportation and reducing dependence on private motorized individual transport, and will consequently change consumer mobility behavior in the future. Despite the growing interest and importance of sustainable transportation modes such as shared micromobility, research still shows gaps in terms of reasons for adoption, outcomes, and the role of user experience in the perception process. To address this gap, we extend the UTAUT2 (Venkatesh et al., 2012) with constructs from the theory of consumer perceived value (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), regulatory focus theory (Avnet & Higgins, 2006; Higgins, 1997) explaining next to the utilitarian path of technology adoption an affective promotion orientated path namely through subjective well-being, a key concept in transformative consumer research theories (Diener et al., 1999; Diener & Chan, 2011), and social identity theory (Ashforth & Mael, 1989). In summary, our research contributes to theory in the following ways.

First, we confirm regulatory focus theory (Higgins, 1997), which argues that there are two types of goals when making decisions to adopt technologies: utilitarian, prevention-oriented goals, and affective, promotion-oriented goals. A utilitarian prevention-oriented focus involves rationality, ease of use, and performance, whereas a promotion-oriented focus involves affective goals, such as hedonism and well-being (Avnet & Higgins, 2006). Based on the UTAUT2 (Venkatesh et al., 2012), we demonstrate that utilitarian, prevention-oriented goals (incorporated through performance expectancy) strongly influence the behavioral intention to use shared micromobility services in a closed-campus environment, whereas effort expectancy and social influence do not. Moreover, based on consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), we confirm that the decisions to adopt micromobility services are affected by affective, promotion-oriented goals (Avnet & Higgins, 2006). We highlight that value dimensions are multiple and user-group dependent in the decision process of intending to use shared micromobility services. We show that hedonic value is a relevant dimension. Using micromobility modes is perceived as fun and enjoyable, and this perception positively influences the decision to use such a service.

Second, we contribute to a recent meta-analysis about technology adoption "encouraging scholars to extend research on outcomes of technology use" (Blut et al., 2021, p. 59), and enhance our model with two context-relevant possible consequences and outcomes of using shared micromobility technology, subjective well-being and organizational identification. Subjective well-being includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction (Diener & Chan, 2011). Indeed, the direction of the relationship between shared micromobility adoption behavior and perceived well-being is unclear in the literature, as the relationship can go both ways. On the one hand, perceived subjective well-being may influence technology acceptance by reinforcing positive mental representations and feelings about the technology (Davis & Pechmann, 2013; Mick, 2012). On the other hand, adoption could also be an important antecedent of perceived well-being, since shared micromobility services can enhance the subjective well-being of the user

(Delbosc & Currie, 2011; Leyden et al., 2011; Woodcock et al., 2014). Based on the recognition, that using more sustainable and more health-oriented active transportation modes like micromobility, can contribute to subjective well-being, we highlight that respondents with higher intentions to use also experience higher improvements in subjective well-being. By empirically investigating this positive relationship in the context of shared micromobility in a closed-campus setting, we contribute to the field of transformative consumer research theories (Diener et al., 1999; Diener & Chan, 2011). Moreover, we show not only the beneficial consequences for users but also a positive outcome for the providing organization of a closed-campus micromobility service. Specific to the context of a closed-campus setting, we include the variable organizational identification, drawn from social identity theory (Ashforth & Mael, 1989; Homburg et al., 2009), and show that the provision of such closed-campus services can positively influence the identification with an organization. In doing so, we contribute to the field of technology research (Blut et al., 2021) by extending research on outcomes of technology use, and to the field of sharing-based consumption (Eckhardt et al., 2019) by including organizational identification as a platform-related outcome for providing organizations. In addition, and based on employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), we show that in organizational, most often professional environments, task enablement is an important antecedent of performance expectancy.

Third, we contribute to theory from a methodological standpoint. A recent meta-analysis about technology adoption calls out that "more research is needed on the changing importance of predictors over time" (Blut et al., 2021, p. 62). Based on two independent samples and a two-wave longitudinal study design, we integrate short-term and long-term user experience effects and show the changing importance of antecedents and outcomes, which is, to our best knowledge, rare in the technology acceptance literature (Taylor & Todd, 1995; Venkatesh et al., 2002). We show that effects are in most cases not only temporary and stable, but evolve (increase or decrease) over time. Moreover, we show that some value dimensions appear only for certain user groups. For example, economic value is a significant and stable variable for younger users for whom the environmental benefits are less relevant. On the other hand, we detect the opposite results for the age- and gender-representative sample in Study 1, where environmental benefits of shared micromobility emerge as significant motivators, but economic benefits not. Moreover, we contribute to an emerging research field that applies PLS-SEM to longitudinal user data (Henseler, 2017; Roemer, 2016). To the best of our knowledge, our research is the first that applied a within-subject longitudinal SEM analysis to investigate antecedents of shared mobility use over time.

6.2 Managerial Contributions

Our research provides managers with an overview of the factors that influence consumers' decision process to use shared micromobility in closed-campus environments. Performance expectancy, task enablement, and perceived hedonic value are the major antecedents of initial micromobility use. Marketers and providers of closed-campus micromobility solutions should highlight these types of benefits in communication by emphasizing how performant and fun it is to use the service. In terms of performance, it is especially beneficial when it improves routes and trips that would have previously been done with individual motorized transport or would have been cumbersome with other modes of transportation. In addition, providing shared micromobility in organizational settings is most effective and powerful when it enables people in their daily routines and work. For example, it is particularly useful where users' work and daily routines require frequent movement between different locations. Therefore, providers should specialize in organizations where the services improve how people work or live. This is often found in urban transportation; therefore these mobility services are particularly useful and valuable for professional environments located in urban areas (e.g., business districts in downtown areas) and for organizations that have a large geographic area (e.g., university campuses, companies with buildings spread across a central location). Moreover, it is important to differentiate the consumer perceived value dimensions, shared micromobility can provide according to different consumer groups. For younger people, economic benefits are more relevant. Marketers should thus pay special attention to the pricing process. Too high prices could diminish the perceived economic value and thereby also negatively influence the subsequent intention to use the service. Perceived environmental value is an important predictor of behavioral intention to use, and should therefore not be underestimated in the marketing and communication process. The service should be designed and marketed in such a way that users perceive the service as environmentally friendly and as an improvement of their mobility behavior in terms of sustainability. In addition, marketing should also emphasize that using these micromobility services can produce positive outcomes, for both end-users and providing organizations. From the perspective of end-users, the use of shared micromobility can contribute to subjective well-being. Marketing should promote these benefits by highlighting that using shared micromobility is physical activity in the open air, which can increase psychological and physical well-being. From the perspective of the providing organization, it should be emphasized that the provision of a closed-campus micromobility service is not only valuable for users' performance and subjective well-being but can also contribute to a positive effect on the relationship between both parties through organizational identification. Organizations should therefore not only show the directly measurable benefits but also position the micromobility service as an enabling (employer) branding tool. Providing shared micromobility services within the enterprise can be a promising investment to differentiate from competitors in the battle for talent and skilled workers. Moreover, as in our investigation, the effect of organizational identification decreases with user experience, we recommend that organizational marketing regularly and actively promote the service and its special features to prevent possible habituation effects. In addition, we want to point out the topic of price mechanism. If the organization subsidizes the use of the service, making it cheaper than available market alternatives, or even free to users, this can certainly have an impact on the perception of economic value and consequently on the willingness of users to use the service.

7 Limitations and Future Research

Although the results of this study provide significant information, there are some limitations to consider that call for future research. The first limitation is due to the time-consuming longitudinal study design, which requires respondents to answer two surveys. Therefore, both of our samples are rather small. Consequently, statistical results are likely to be biased due to our sampling procedure. However, we attempted to conduct a deliberate sample representative of the German working population in Study 1 with external, non-registered users. Second, we did not control for time differences between the first survey, the test, and the second survey because of the limited testing period in Study 1. Although we tried to standardize the research design situation, there may be bias due to other conditions. For example, biases may result due to weather and the daytime of the test experience, for which we have not further controlled in Study 1. Third, we did not control for real use frequency and the personal situation of the respondents in Study 2. For example, respondents' evaluation in the post-use survey may be influenced by the frequency of real use, which we did not control for. In addition, the number of semesters and previous progress at the university may influence students' perceptions of certain constructs, and how they evolve. Moreover, we did not include the variable of subjective well-being in Study 2. The effect of long-term experience on the perception of subjective well-being as an outcome could therefore not be analyzed. Therefore, future studies should address this gap in the analysis of long-term perceptions of subjective well-being as an outcome. Fourth and finally, the test service DHBW Drive is strongly associated with e-scooters, which are controversial in the public view. Micromobility is more than only e-scooters and is particularly useful to solve the last-mile problem for different purposes. Understanding usage purposes could provide information to derive user types and information for service and product design. Therefore, future research should consider other modes of micromobility transportation (e.g., electric cargo bikes) and investigate the connection between transportation mode, travel purposes, adoption factors, and intention to use the service.

8 Summary of the Chapter

This chapter has focused on understanding the dynamic adoption and outcomes of closed-campus micromobility services based on short-term and long-term user experience. Based on the unified theory of acceptance and use of technology (UTAUT2; Venkatesh et al., 2012), we established an enhanced model with context-specific constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), theory of well-being (Diener et al., 1999; Diener & Chan, 2011) and social identity theory (Ashforth & Mael, 1989). To test the model and check for longitudinal effects of user experience, we used a two-wave within-subject survey design with two independent samples and an evolutional path modeling approach for panel data (Roemer, 2016) in partial least square structural modeling. Our findings indicate that performance expectancy and task enablement are stable predictors of usage intention that do not change with user experience. On the other hand, we find that hedonic value is an important predictor before using the service. However, its importance diminishes as the level of user experience increases. In addition, we find that perceived economic value and perceived environmental value are stable antecedents, but they depend on the user segment being studied. In terms of consequences and outcomes, we highlight the role of subjective well-being, which is an important and stable outcome. Finally, we show that organizational identification is a significant outcome before using, but is not significant in either sample after using the service.

The final part of the paper represents our overall conclusion, in which we present a discussion of the theoretical, methodological, managerial, and societal contributions, the limitations of our research, and future research directions.

Introduction

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A Literature Review of the Sharing Economy from the Marketing Perspective: a Theory, Context, Characteristics, and Methods (TCCM) Approach

Chapter 2.
Antecedents of Adoption and Usage of Closed-campus Micromobility

Chapter 3.
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Conclusion

Conclusion

This research explores how consumers use and interact with shared mobility, focusing on a very new and little-researched application: closed-campus micromobility. The first chapter is a conceptual paper in which we conduct a systematic literature review and begin to define our research questions. We select 88 peer-reviewed papers published in the field of marketing and consumer behavior literature dealing with the sharing economy. Based on the theory-context-characteristics-methodology (TCCM) review protocol (Gilal et al., 2019; Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018) we highlight both the theoretical and empirical aspects of the given research area. Finally, the first chapter presents a research agenda that supports the scientific community with new directions in research at the intersection of marketing and the sharing economy. Moreover, the derived future research directions are the basis for the upcoming chapters of the thesis.

In Chapter 2, we investigate predicting factors of the initial adoption of a shared micromobility innovation in a professional, closed-campus environment. Drawing from the well-established UTAUT2 framework (Venkatesh et al., 2012), we integrate antecedents from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), and trust-risk theories (Martin & Murphy, 2017; Pavlou, 2003). Based, on a study with registered users of DHBW Drive (N=199), a field laboratory for micromobility in closed-campus environments, we tested our model with survey data and real-world behavioral data. This approach allows us to examine not only the initial intention to use the service, but also whether actual real usage behavior is influenced.

In Chapter 3, we investigate factors that influence the satisfaction and continuance intention of using closed-campus micromobility as the long-term viability of a new product or service also depends on the continuity of user behavior (Bhattacherjee, 2001; Venkatesh et al., 2011). To do so, we develop a model based on the expectation-confirmation model

(Bhattacherjee, 2001) and integrate constructs from consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988) and the theory of well-being (Diener et al., 1999; Diener & Chan, 2011). To test the model, we conducted again a survey study with registered users of DHBW Drive (N=231) to analyze continuance intention that we combined with behavioral data from DHBW Drive to investigate real continuance use of closed-campus micromobility.

In the last Chapter 4, we implement within-subject designs to finally investigate longitudinal effects and to see how consumers' evaluation of predictors and outcomes of shared micromobility innovations evolve with the user experience of a closed-campus micromobility solution. To enhance external validity, we conducted two independent two-wave longitudinal studies: a representative sample study with inexperienced, external people who did test the service of DHBW Drive (Study 1 – short-term user experience), and an internal sample of registered users of DHBW Drive (Study 2 – long-term user experience). To test for longitudinal user experience effects in both studies, we use an evolutional path modeling approach for panel data (Roemer, 2016) implemented with partial least squares structural equation modeling (PLS-SEM).

1 Theoretical contributions

1.1 Mapping the Sharing Economy in Marketing Research

Through our systematic literature review, we contribute to theory by providing a holistic overview of theoretical and empirical aspects of marketing and consumer behavior research on the sharing economy as a whole and outline future research directions that support the advancement of the research field. The review paints a comprehensive picture of the current state of marketing and consumer behavior research literature on the sharing economy. Following the TCCM protocol (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019; Rosado-Serrano et al., 2018) and by reviewing 88 peer-reviewed articles on key theoretical and empirical aspects, our review shows that the research is still in its infancy and has only recently begun. The studies analyzed draw on a wide range of individual theories, most of which examine user- and exchange-related psychological processes. Most of the studies are from Western industrialized countries, mainly the United States and Germany, and focus on a small group of industries, mainly the accommodation, car and ride sharing sectors. Our detailed examination of the characteristics analyzed shows that research has focused on the user- and exchange-related variables, while platform-related and other groups of variables (i.e., industry) play a minor role. Due to the novelty of the research area, we found many qualitative and conceptual studies in addition to the predominant quantitative research, resulting in different methodologies. Second, based on the findings and evolving directions, we set a future research agenda that outlines several themes based on the TCCM structure. On the theoretical side, we propose the use of theories that better account for the specific environment of the sharing economy and the different perspectives on sharing. In particular, theories that incorporate the platform as a mediator could improve future studies that examine the impact of the platform on users' beliefs and behaviors, and moreover, examine the outcomes for the platform perspective. In terms of context, most related research has been conducted on accommodation, car or ride sharing, which include the most well-known real-world examples (e.g., Airbnb). However, sharing platforms can be found in many sectors, and even in the well-known sectors, the research field is constantly evolving, and many aspects are not yet sufficiently explored. Therefore, more research in these sectors is desirable but should be complemented by research in other contexts (e.g., shared micromobility). Finally, platform-related outcomes and industry- or country-related variables have been less considered in past research and should be given more consideration. Regarding the methods used, few studies use secondary data and real behavioral data, and many studies rely on single-source data to test their hypotheses, especially in the context of surveys. In addition, we found only one study that examined the impact of sharing-based consumption over time. To reduce the problems of single-source designs and to increase validity, future research would benefit from multiple-source designs, the inclusion of real-world user behavior data, and longitudinal data analysis

1.2 Investigating Initial Adoption and Real Use Behavior

To the best of our knowledge, we are the first to systematically and empirically study antecedents of initial adoption intention and real use of closed-campus micromobility in a professional, organizational environment, a new and promising application of shared micromobility. By enhancing the well-established UTAUT2 model (Venkatesh et al., 2012) with new and rarely investigated antecedents specific to the context and testing our conceptual model, our research contributes to theory in the following ways. First, we highlight the relevance of cognitive antecedents of usage intention and real use of a closed-campus micromobility service. In line with previous research about the adoption of shared micromobility, we show that performance expectancy and effort expectancy are both significant antecedents of behavioral intention to use closed-campus micromobility. However, we do not detect this relationship for social influence. We thus contribute to the literature by demonstrating that the adoption of shared micromobility in closed campus environments is based on cognitive rather than social considerations (Bandura, 1989).

Moreover, specifically for the context, we enhance the model with the cognitive variable drawing from employee enablement theory (Adler & Borys, 1996; Permana et al., 2015). In this way, we show that expected performance is strongly influenced by perceived enablement in daily tasks. In an organizational closed-campus context, the more users perceive the mobility service as an enabling and helpful tool provided by the organization, the more performant the perception will be, and the more likely the user will be to use it. We thus contribute to the literature on shared micromobility in the closed-campus context by demonstrating the importance of perceived enablement for the performance perception of the provided service.

Furthermore, we show that in addition to the cognitive variables of performance and effort expectancy (Venkatesh et al., 2012), different consumer perceived value dimensions (Holbrook, 1994; Zeithaml, 1988) influence the decision to use the shared micromobility service. Previous research on shared micromobility has discussed the multiple added values that such services can provide to users (Abduljabbar et al., 2021; Buehler et al., 2021). Based on our empirical study, we demonstrate the importance of hedonic and utilitarian values for the decision to use micromobility in closed-campus settings. However, we could not detect this relationship between the economic and environmental value for users. Since the significance level for the relationship between economic value and behavioral intention to adopt is just above the recommended threshold and there are reasonable explanations for the insignificant influence of the ecological value, we nevertheless believe that our research is pointing in the right direction. Accordingly, our results contribute to the understanding of antecedents of the adoption of closed-campus micromobility and show that hedonic and utilitarian value (Babin et al., 1994) are important concepts to enhance the behavioral intention to use a closed-campus micromobility service.

Finally, concerning technology adoption research (Bhattacherjee & Lin, 2015; Blut et al., 2021; Taylor & Todd, 1995), we contribute to the literature by empirically confirming the positive causal relationship between survey-measured, declarative behavioral intention to use the closed-campus micromobility service and real use behavior, which was measured with real behavioral data of DHBW Drive. This, in fact, reinforces the relevance of real usage data (e.g., from field laboratories) with technology acceptance models (Blut et al., 2021).

1.3 Exploring Satisfaction and Real Continuance Behavior

Similar to the investigation of initial adoption intention, and the best of our knowledge, we are the first to systematically and empirically investigate satisfaction and continuance behavior of closed-campus micromobility. Therefore, we contribute to the literature on service satisfaction and continuance intention of new technologies (Bhattacherjee & Lin, 2015) in the following ways. First, we enhance the ECM (Bhattacherjee et al., 2012) with the variable of subjective well-being (Diener et al., 1999), thereby also contributing to transformative consumer research (Davis et al., 2016; Zeng & Botella-Carrubi, 2023). In our model, we emphasize the importance of affective perceptions in the form of subjective well-being (Diener et al., 1999) and its effect on satisfaction, and continued use behavior (Bhattacherjee, 2001). Since well-being is a significant predictor of satisfaction and continuance intention but performance expectancy is not, we show that in certain situations the perception of improved subjective well-being may be more important than improved performance. The more well-being users expect when using a closed-campus micromobility service, the more they will develop positive feelings and satisfaction with the service, and the more they should intend to use this technology.

In addition, we extend the ECM with constructs from the theory of consumer perceived value (Holbrook, 1994; Zeithaml, 1988). We highlight the manifold value dimensions perceived by consumers (namely hedonic, economic, environmental, and utilitarian value) as significant antecedents of subjective well-being and performance expectation of micromobility services in closed-campus settings. In terms of subjective well-being, we demonstrate that both hedonic value (Babin et al., 1994) and economic value (Venkatesh et al., 2012) positively influence the perception of subjective well-being (Diener et al., 1999). The more users perceive the service as fun and economically useful, the more they will judge the mental, psychological, and physiological benefits of the service in terms of their own subjective well-being (Ma et al., 2018; Zhang et al., 2017). Moreover, if the use of a micromobility service on the closed campus improves the cost-benefit ratio compared to previous or alternative transportation options, people develop positive feelings about the service in terms of their personal subjective well-being (Jorgensen et al., 2010). In addition to the relationships with subjective well-being, we show that utilitarian value and environmental value are relevant predictors of perceived performance expectancy. The more users perceive the use of the service as a convenient (Lyu & Zhang, 2021; Ye, 2022) and green mode (Chen, 2016; Flores & Jansson, 2021) of transportation, the more they will perceive it as an improvement in terms of efficient and effective travel. Therefore, we contribute to the literature by highlighting the manifold consumer perceived value dimensions in the process of building continuance intention to use the closed-campus micromobility service.

Finally, we contribute to the field of adoption and continuity behavior research literature (Bhattacherjee & Premkumar, 2004; Blut et al., 2021; Venkatesh et al., 2011) by empirically testing the causal relationship of continuance intention on real continuity use behavior. Although the results of our model testing exceed the mostly applied significance level of .05 (5%), the in social science accepted significance level of .10 (10%) is reached (Labovitz, 1968; Nelson et al., 1986; Nickerson, 2000). Our results underline the relevance of real-world behavioral data (e.g., from field laboratories) for technology acceptance models, and can therefore be considered as an additional methodological-theoretical contribution.

1.4 Considering the Effects of User Experience on Adoption and Outcomes

Recent research on the adoption of new technologies, products, and services suggests that the importance of predictors of adoption changes over time and calls for investigating temporal issues in empirical adoption research (Blut et al., 2021; Venkatesh et al., 2021). We contribute to this research gap in the following ways. First, by investigating adoption factors over time, we confirm regulatory focus theory (Higgins, 1997), which argues that there are two types of goals when making decisions to adopt technologies: utilitarian, prevention-oriented goals, and affective, promotion-oriented goals. Based on the UTAUT2 (Venkatesh et al., 2012) and employee enablement theory (Adler & Borys, 1996; Permana et al., 2015), we demonstrate that utilitarian, prevention-oriented goals (incorporated through performance expectancy and task enablement) are a strong and stable predictor of usage intention for the behavioral intention to use shared micromobility services in a closed-campus environment. Our findings indicate that performance expectancy and task enablement are stable predictors of usage intention that do not change with user experience. Moreover, based on consumer perceived value theory (Holbrook, 1994; Zeithaml, 1988), we confirm that decisions to adopt micromobility services are affected by affective, promotion-oriented goals (Avnet & Higgins, 2006). We highlight that value dimensions are multiple and user-group dependent in the decision process of intending to use shared micromobility services. We show that hedonic value is a relevant dimension, but might be a sensitive predictor. Before use experience, hedonic value is a significant antecedent of behavioral intention, but this effect diminishes as the level of user experience increases. In addition, we find that perceived economic and environmental values are stable antecedents, but depend on the sample and user segment studied. Economic value seems to be a stable and important factor for young populations, while environmental value is a stable factor for age-representative populations.

Second, we enhance our model with two context-relevant possible consequences and outcomes of using shared micromobility technology, and, thus, contribute to research on outcomes of technology use (Blut et al., 2021, p. 59). We include subjective well-being and organizational identification as outcomes in our model. Subjective well-being includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction (Diener & Chan, 2011). The direction of the relationship between shared micromobility adoption behavior and perceived well-being is unclear in the literature, as the relationship can go both ways. On the one hand, perceived well-being may influence technology acceptance by reinforcing positive mental representations and feelings about the technology (Davis & Pechmann, 2013; Mick, 2012). On the other hand, adoption could also be an important predictor of perceived well-being, since shared micromobility services should enhance the subjective well-being of the user (Delbosc & Currie, 2011; Leyden et al., 2011; Woodcock et al., 2014). Based on the recognition that using more sustainable and more active transportation modes like micromobility can contribute to subjective well-being; we highlight that people who express higher intentions to use also experience improved subjective well-being. Concerning use experience effects, subjective well-being turns out to be an important and stable outcome. Moreover, we investigate not only beneficial outcomes for users but also positive consequences for the providing organization of a closed-campus micromobility service. By doing so, we contribute to the research gap of investigating possible platform-related outcomes that we identified through our systematic literature review in Chapter 1. Specific to the context of closed-campus solutions, we include the variable organizational identification, drawn from social identity theory (Ashforth & Mael, 1989; Homburg et al., 2009), and show that the provision of closed-campus services can positively influence the identification with an organization. However, similar to hedonic value, this effect decreases with increasing user experience, as for both samples we detect no significance in the models after user experience.

2 Methodological Contributions

The first methodological contribution relates to the multiple-source data design used in the empirical investigations. In particular, we combined declarative survey data with real use behavioral data. Our review of the literature on marketing and consumer behavior in the sharing economy concludes that few studies use data on real use behavior and that many studies rely on single-source data to test their hypotheses, particularly in the context of surveys. Furthermore, the meta-analyses of Blut et al. (2021) strongly recommend the use of real-world usage data to test technology adoption models. While survey data can, for instance, offer high levels of internal validity, data on real use behavior offer higher levels of external validity and are important for testing the generalizability of findings in real-world settings. Moreover, single-source data designs often raise issues of common-method bias that can harm the validity of estimated parameters. Multiple-data source design is an effective way to avoid such biases (Podsakoff et al., 2003). By using behavioral data about real use behavior, provided by the field laboratory of DHBW Drive, we contribute to this methodological research gap by demonstrating the causal relationship that intention to use indeed impacts real use behavior.

Moreover, we make a second important methodological contribution by conducting a longitudinal within-subject field study and examining consumers' responses to real use experiences (short-term and long-term) over time. Thanks to the field laboratory DHBW Drive, we investigate how users' perceptions evolve with increasing use experience. We propose that such an examination of adoption depending on real user experience can lead to more in-depth insights than the prevailing static approaches. Moreover, the longitudinal field study approach helps to overcome the limitations of online-based surveys, where respondents often do not have a consistent impression of the survey subject. From a methodological perspective, we thus contribute to a critical research gap that addresses the changing importance of predictors over time and above all over a long period, namely one year (Blut et al., 2021; Venkatesh et al., 2021). Another contribution in terms of longitudinal studies can be seen in the data analysis approach. We apply a little-used approach to analyze longitudinal panel data with partial least squares structural equation modeling (PLS-SEM; Roemer, 2016). In this way, we contribute to a research field consisting of relatively few publications that apply PLS-SEM to longitudinal data (Henseler, 2017).

3 Managerial Contributions

Implementing and introducing sharing-based services requires the attention of managers and practitioners, who should carefully consider the needs of consumers to ensure successful and positive interactions with the service and high user rates. We provide important managerial insights from both, the consumers' and the organizations' perspectives for corporations seeking to implement shared micromobility in closed-campus environments, and for managers working in the broader context of shared mobility innovation.

From the consumers' perspective, the strongest predictors of initial micromobility adoption are performance expectancy, task enablement, and perceived hedonic value. Marketers and providers of micromobility solutions should emphasize these types of benefits in their communications by highlighting how performance and enjoyment of the service look like and what consumers can expect. In terms of performance, it is particularly beneficial when it improves routes and trips that were previously restricted to individual automobiles or inconvenient for other modes of transportation. In addition, shared micromobility in professional settings is most effective and powerful when enabling people in their everyday lives and jobs. For example, it is particularly useful when users are frequently in transit between different locations as part of their daily work and private routines. Therefore, providers should focus on organizations where the services improve the performance of users because of their daily work or life. This is often the case in urban transportation. Therefore, such services are particularly useful and valuable for professional environments located in urban environments (e.g., business districts in city centers) and for organizations with high geographical coverage (e.g., university campuses, companies with buildings distributed in a central location). In addition, we show that micromobility services in a closed campus environment can provide additional differentiated consumer value based on potential user groups. For younger organizations, economic benefits are more relevant. Marketers should pay special attention to the pricing process for such organizations. If the price is too high, the perceived economic value of the product may be reduced, thus negatively impacting subsequent usage intention. In addition, the perceived environmental value is an important predictor of behavioral intention to use and should not be underestimated in the marketing process. The product should be designed and promoted in such a way that potential users perceive the service as environmentally friendly and as an improvement in their sustainable mobility behavior, which may lead to an increased willingness to use the service. Finally, using the longitudinal analysis, we find a significant positive increase in perceived hedonic value, effort expectancy, and behavioral intention to use after experiencing the test. Moreover, we find a positive trend for performance expectancy and task enablement. Therefore, we suggest that experiencing the service through an easily accessible product trial can help shape stronger consumer beliefs.

In addition, we want to highlight the managerial contributions from the organizations' perspective. We suggest that marketing should indicate that the use of the service can lead to positive outcomes for the cooperations providing it. The use of a shared micromobility service can be a contributor to the subjective well-being of the organizational members. Marketing should promote these benefits, emphasizing that shared micromobility is an active mobility mode that can improve mental and physical health. Moreover, it can reduce the reliance on individual cars and thus lead to more flexible and sustainable mobility behavior, which in turn can generate benefits for the organization (e.g., less parking space) of the organization. Additionally, we investigate and highlight the importance of organizational identification, defined as "the extent to which a person senses a oneness or sameness with the organization" (Korschun et al., 2014, p. 21). Providing a shared micromobility service is not only valuable for the performance and subjective well-being of the users, but it can also strengthen the identification of the users with the providing organization. Therefore, in addition to weighing the directly measurable benefits against the potential costs, providers should also consider the shared micromobility service as an organizational (employer) branding service. This can be a promising investment in differentiation at a time when companies are finding it increasingly difficult to find qualified professionals. Since the effect of organizational identification in our study decreases with increasing experience, we recommend that organizational marketing should regularly and actively promote the service and its features to users to prevent possible habituation effects. In addition, we suggest drawing managerial attention to the price mechanism of closed-campus micromobility services. If the organization subsidizes the service in such a way that it is cheaper than available market alternatives or even free of charge for users, this will certainly have an impact on the perception of economic value, consequently on the willingness of users to use the service, and ultimately on the identification of users with the organization.

4 Societal Contributions

Finally, we want to highlight the societal contributions and recommendations for policymakers. Forms of shared mobility have already changed the mobility behavior of many people worldwide and will continue to influence our society in terms of their mobility behavior in the future, as they are more sustainable, more flexible, and more focused on the purpose and destination of the trip than previous forms of mobility. Moreover, the enhanced use of shared mobility can contribute to the Sustainable Development Goals (SDGs) of the United Nations (Chaudhuri et al., 2022; Lukasiewicz et al., 2022), including good health and well-being (SDG3), sustainable cities and communities (SDG 11), and responsible consumption (SDG 12). In this context, policymakers need to make influential and effective decisions that take into account the challenges that shared mobility, and in particular shared micromobility, pose due to their specific characteristics. According to our results, shared micromobility can contribute to users' subjective well-being when it is perceived as a performant, enabling, sustainable, economic, and enjoyable form of mobility that can promote users' mental and physical health. However, this perception depends not only on the mode of transport itself but also on the environmental parameters of its use. To ensure long-term success and exploit the full potential of shared micromobility, policymakers should therefore create the appropriate policy parameters. As performance expectancy is a strong and stable predictor of adoption, policymakers should consider infrastructural aspects of the operation and parking of micromobility devices. Research states that the most difficult challenges of the introduction of micromobility services are to locate parking and operation space for the micromobility devices (Abduljabbar et al., 2021; Bozzi & Aguilera, 2021). Closed-campus micromobility are pre-delineated solutions, only available to a respective community (e.g., university, office campus, residential quarter). Usually, they are operated as station-based or hybrid solutions, so that users access and return the micromobility device at fixed stations or at any location within a predefined geographic region of the organization. One challenge of such geographically restricted solutions might be the connection to public infrastructure, for instance, when users want to use the shared micromobility service in a multi-modal combination with public transportation. Therefore, the provision of designated supportive infrastructure, in locations where it makes sense to users and providing organizations (e.g., near public transport stations), may help to increase the courage to provide and use shared micromobility services. For example, a study in four cities in the United States found that parked cars are a far greater barrier to on-street transportation than micromobility modes (e.g., bicycles and e-scooters), and suggested that policymakers should take a more comprehensive approach to parking space aligned for all modes of transportation (Brown et al., 2020). The study also found that micromobility users use parking infrastructure when it is adequately provided. This would also result in clear-defined and greater accessibility of shared micromobility, which in turn can lead again to an increased and better perception of performance expectancy. Moreover, based on our results, hedonic and environmental motives are influencing consumer adoption behavior. Although the recent public discussion about shared micromobility, our results confirm that closed-campus micromobility is perceived as an enjoyable, convenient, and green mobility solution. However, a challenging issue of enjoyment regarding shared micromobility is traveling safety. To promote positive and green feelings towards shared micromobility and reduce safety concerns, research concludes that urban policymakers should dedicate more space to micromobility modes, introduce traffic-calmed zones, and reduce car speed limits on urban-centered roads (Gössling, 2020; Laa & Leth, 2020). This could not only help mitigate the current challenges posed by different forms of micromobility but also create better conditions for walking while contributing to a more sustainable and joyful public perception of shared micromobility modes.

5 Limitations and Future Research Directions

Although our results provide valuable information, there are some limitations that open new avenues for future research. Considering our research approach and findings in the TCCM literature review, this study is not without limitations. First, the systematic literature search may seem not comprehensive or inappropriate because we only searched in journals related to the marketing and consumer behavior research field. However, the sharing economy is a research area with practical applications in different industries and sectors, and adoption factors are influenced by the applications. Therefore, future research on marketing and consumer behavior in terms of shared mobility should consider all available sources of literature.

Regarding the research design of the empirical studies in Chapters 2, 3, and 4, we also address possible limitations. Some limitations might result due to our sampling process in cooperation with the field laboratory DHBW Drive. First, we only surveyed registered users of DHBW Drive and did not include members of DHBW who were unfamiliar with the service or who deliberately did not register. This can lead to bias or an excessively positive rating, as people who have registered for the service are more likely to provide good evaluations than people who have not. Second, our internal samples are relatively young and mostly students. Although younger people samples offer a prospective market for the adoption of new mobility technologies, they are typically also more drawn to new technology, goods, and services (Ashraf et al., 2014; Barbosa et al., 2019; Mcmillan & Morrison, 2006; Meyer-Waarden & Cloarec, 2022). This in turn can lead to an overvaluation of potential relative factors. Future research should therefore investigate closed-campus micromobility and shared micromobility in different settings, e.g., office campuses, tech parks, residential neighborhoods, and municipalities. Third, the findings of our studies may be limited due to the relatively small sample sizes. Determining an appropriate sample size is vital to ensure the quality and rigor of any study. According to Hair et al. (2014), the minimum sample size should be 10 times the largest number of structural paths directed toward a particular construct in a structural model. We achieved this minimum sample size for all of our studies. However, some references require a minimum sample size of 200 to reduce biases to an acceptable level (Kline, 2016), and sample sizes should be at least 10 to 15 times the number of observed variables (Stevens, 2002).

Some limitations might also arise from using the project DHBW Drive as an application example and case study. First, DHBW Drive operated in a highly appropriate environment. On the one hand, and due to its geographic basin topology and an increased commuter volume, the city of Stuttgart is a generally good use case for shared micromobility; on the other hand, the distributed location of the DHBW university campuses in the Stuttgart city center provides ideal conditions for closed-campus mobility needs. This might again have resulted in a biased and non-representative perception. Second, and in Chapter 4, there may be limitations due to the standardized test track. For example, there may be bias due to weather and time of day of the testing experience, which we did not control. In addition, the sample sizes are rather small, which again may have introduced bias. Third, DHBW Drive was strongly associated with e-scooters because other modes of transportation were not included. However, e-scooters are controversial among the public and do not represent the overall subject of shared micromobility. Future research should also consider other modes of micromobility transportation (e.g., electric bicycles, cargo bicycles) to paint a holistic picture of the overall subject.

Finally, there might also be limitations due to our research design. First, we focused our research on factors that influence initial adoption intention and continuance intention to use closed-campus micromobility innovations. Understanding usage purposes could provide information to derive user types and information for service and product design. Therefore, future research should investigate the connection between transportation modes, travel purposes, and intention to use the service. Second, our models strongly focus on antecedents that positively impact intentions to use. However, future research should also account for additional variables that are barriers and potentially decrease intentions to use and outcomes of shared micromobility use, such as types of risks (e.g., safety concerns). Third, we did not include the variable of subjective well-being in the internal sample of our longitudinal analysis and did not investigate the long-term longitudinal effects of user experience on subjective well-being. Therefore, future longitudinal field studies about shared micromobility should consider subjective well-being in their research design and investigate longitudinal effects on users' perception of subjective well-being. Fourth and finally, future research should analyze other consequences of shared micromobility usage, e.g., to what extent the intention to use shared micromobility is positively associated with a reduction of motorized individual transport and increased use of public transport.

Finally, considering the contribution gaps identified in Chapter 1 and the scope of the underlying thesis, we want to highlight some future research directions. First, although we have included platform-relevant characteristics in our study (e.g., technology trust as an antecedent or organizational identification as an outcome), we still see gaps for contribution from a platform perspective. For the sustainable operation of shared micromobility services in closed-campus settings and in general, the service provider needs to create and retain a critical mass of users. Our findings provide important information about what factors influence the decision to adopt and continue using the service, and how these perceptions are influenced by the users' experience. Based on these results, and to gain further insights from the platform's perspective, we propose empirical work that, for example, evaluates platform marketing activities in terms of how they may influence users' perceptions and, consequently, their intention to use the service. Moreover, we suggest a stronger integration of platform-related variables. Especially, in the case of shared micromobility, stronger integration of platform or service-related variables could enhance understanding of adoption behavior. For example, an investigation of how the type of accessibility of the service (open; membership; organizational) can influence the antecedents and outcomes of shared micromobility service, might be useful to further innovate this type of service. Moreover, the influence of platform governance and service design should be considered. For example, how users' perceptions differ depending on the recent public discussed operation models of station-based and dockless micromobility services. Finally, regarding contribution gaps in terms of methodology, we propose the use of big data sources like posts, comments, news, and other textual artifacts about shared micromobility services which can be analyzed with qualitative approaches to validate the findings of quantitative studies. For example, text mining analytics can identify latent structures and can generate influential insights for marketing and consumer behavior (Humphreys & Wang, 2018). We emphasize that our models may not cover all relevant topics related to the adoption of micromobility sharing. Future research could collect data from additional secondary netnographic sources (e.g., online social networks) to confirm and extend our findings. This could also explore how consumers perceive current regulations and policies on micromobility sharing (e.g., the ban on e-scooters in Paris), and could provide important insights for the further sustainable development of these services.

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ABSTRACT

As an application of the sharing economy, shared micromobility refers to the shared use of light-weight transportation modes (e.g., e-scooter sharing). It is considered an integral part of sustainable urban mobility, as it reduces the reliance on individual motorized vehicles and solves the first-and-last-mile problem of public transportation. However, shared micromobility is controversial with consumer-related issues. Consequently, it has attracted interest outside and inside academia, and service providers innovate their solutions. In this context, this dissertation aims to understand how consumers adopt innovative shared micromobility by focusing on the application in closed-campus environments. First, we use the theory–context–characteristics–methodology systematic literature review protocol (Paul & Criado, 2020) to provide a holistic overview and research agenda of theoretical and empirical aspects at the intersection of marketing research on the sharing economy. Thus, we define our research questions related to 1) adoption factors and real user behavior 2) satisfaction and continuance intention to use 3) longitudinal effects of user experience on the perceptions of closed-campus micromobility. By setting up a field laboratory for shared micromobility in a closed-campus setting, we collect empirical survey and behavioral data to answer the related questions. Regarding the first question, we examine the antecedents of behavioral intention to adopt closed-campus micromobility and its influence on real user behavior. We draw on the UTAUT2 (Venkatesh et al., 2012) and integrate consumer perceived value theory (Holbrook, 1994), employee enablement theory (Adler & Borys, 1996) and privacy calculus theory (Martin & Murphy, 2017). The results indicate that performance expectancy, effort expectancy, task enablement, and hedonic and utilitarian value are significant antecedents of behavioral intention, which positively affects real use. Regarding the second question, we examine the antecedents of satisfaction and continuation behavior of closed campus micromobility. We draw on the expectation-confirmation model (Bhattacherjee, 2001) and integrate the theory of well-being

(Diener et al., 1999) and consumer perceived value theory (Holbrook, 1994). The results reveal that subjective well-being is an antecedent of service satisfaction, which in turn is influenced by hedonic and economic values. Finally, regarding the third question, we examine the longitudinal effects of user experience. Based on UTAUT2 (Venkatesh et al., 2012) and regulatory focus theory (Avnet & Higgins, 2006), we add consumer perceived value theory (Holbrook, 1994), employee enablement theory (Adler & Borys, 1996), theory of well-being (Diener et al., 1999) and social identity theory (Ashforth & Mael, 1989). Through a within-subject design and two independent samples (short-term and long-term experience), we reveal that performance expectancy and task enablement are stable antecedents of usage intention, whereas hedonic value decreases. Concerning outcomes, we highlight the role of subjective well-being and organizational identification from the perspective of users and organizations. Our research offers contributions to the literature on technology adoption and shared micromobility, by highlighting important factors and outcomes that influence the decision to use shared micromobility solutions in closed-campus settings. We also offer methodological contributions. Thanks to the implementation of the field laboratory, we combine declarative survey data with real behavioral data and analyze longitudinal effects. To conclude, we present implications for both managers and policymakers who want to implement shared micromobility services.

Keywords: sharing economy; shared micromobility in closed-campus settings; UTAUT2; consumer value; well-being; perceived risks; social impact; user experience; field study; behavioral data; longitudinal analysis

RÉSUMÉ

En tant qu'application de l'économie collaborative, la micromobilité partagée se réfère à l'utilisation partagée de modes de transport légers, tels que le partage de scooters électriques. Elle est considérée comme faisant partie intégrante de la mobilité urbaine durable, car elle réduit la dépendance aux véhicules motorisés individuels et résout le problème du premier et du dernier kilomètre des transports publics. Cependant, la micromobilité partagée est controversée en raison de problèmes liés aux consommateurs, tels que le vandalisme. Par conséquent, elle a suscité de l'intérêt dans le monde académique et du management des fournisseurs de services de solutions de mobilité. Dans ce contexte, cette thèse vise à comprendre comment les consommateurs adoptent la micromobilité partagée en se concentrant sur les environnements de campus fermés. Tout d'abord, nous utilisons le protocole d'analyse de revue de littérature systématique théorie-contexte-caractéristiques-méthodologie (Paul & Criado, 2020) pour donner une agenda de recherche en marketing sur l'économie du partage et la micromobilité. A partir de cette révue de littérature, nous définissons nos questions de recherche sur la micromobilité, précisément sur : 1) les facteurs d'adoption sur a) l'intention d'utilisation de la micromobilité et b) le comportement réel d’utilisation, 2) les antécédents de la satisfaction et l’impact sur comportement d'utilisation, et 3) les effets longitudinaux de l'expérience de l'utilisateur sur l'intention d'utilisation de la micromobilité. En mettant en place un terrain expérimental pour la micromobilité partagée dans un campus fermé, nous recueillons des données d'enquête empiriques et des données comportementales pour répondre à nos questions de recherche. En ce qui concerne la première question à propos des facteurs d'adoption sur a) l'intention d'utilisation de la micromobilité et b) le comportement réel d’utilisation, nous utilisons l'UTAUT2 (Venkatesh et al., 2012) et intégrons la théorie de la valeur perçue (Holbrook, 1994), la théorie de l'engagement organisationnel (Adler & Borys, 1996) et la théorie du calcul de la protection de la vie privée (Martin & Murphy, 2017). Les résultats

indiquent que l'espérance de performance, l'espérance d'effort, l'empowerment de la tâche ainsi que la valeur hédonique et utilitaire sont des antécédents de l'intention d'utilisation de la micromobilité qui affectent ensuite positivement l'utilisation réelle.

En ce qui concerne la deuxième question à propos des antécédents de la satisfaction et l'impact sur comportement d'utilisation de la micromobilité dans les campus fermés, nous utilisons le modèle de confirmation des attentes (Bhattacherjee, 2001) et intégrons la théorie du bien-être (Diener et al., 1999). Les résultats révèlent que le bien-être subjectif est un antécédent de la satisfaction, qui est elle-même influencée par les valeurs perçues hédoniques et économiques. Enfin, En ce qui concerne la troisième question à propos des effets longitudinaux de l'expérience de l'utilisateur sur l'intention d'utilisation de la micromobilité nous utilisons le modèle UTAUT2 (Venkatesh et al., 2012), la théorie de la focalisation réglementaire (Avnet & Higgins, 2006), la théorie de la valeur perçue (Holbrook, 1994), la théorie de l'engagement organisationnel (Adler & Borys, 1996), la théorie du bien-être (Diener et al., 1999) et la théorie de l'identité sociale (Ashforth & Mael, 1989). À travers d'une étude intra-sujet et deux échantillons indépendants (expérience à court terme et à long terme), nous révélons que l'attente de performance et l'empowerment de la tâche sont des antécédents stables de l'intention d'utilisation des services de micro mobilité dans des campus fermés, tandis que la valeur hédonique diminue avec le temps. Nous soulignons le rôle important du bien-être subjectif et de l'identification organisationnelle du point de vue des utilisateurs et des organisations. Notre recherche apporte des contributions à la littérature sur l'adoption des services de micromobilité partagée dans des environnements de campus fermés, en mettant en évidence les facteurs d'adoption qui influencent les décisions d'utiliser ces solutions. Nous faisons également des contributions méthodologiques. Grâce à la mise en place d'un laboratoire expérimental dans un campus fermé, nous combinons des données d'enquête déclaratives avec des données comportementales réelles et analysons les effets longitudinaux de l'utilisation des services de

micro mobilité. En conclusion, nous présentons des implications pour des mangers et les décideurs politiques qui souhaitent mettre en œuvre des services de micromobilité partagée

Mots clés: Économie collaborative ; micromobilité partagée dans campus fermé ; UTAUT2; valeur du consommateur ; bien-être; risque perçu ; impact social; effets de l’expérience utilisateur; étude de terrain ; données comportementales ; analyse longitudinale