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MASTER THESIS

DUOMENIMIS GRĮSTI KLIENTŲ VERTĖS VEIKSNIAI: DALIJIMOSI EKONOMIKOS PLATFORMŲ KLIENTŲ DUOMENŲ PANAUDOJIMAS VERTĖS KŪRIMUI DIDINTI	**DATA-DRIVEN CUSTOMER VALUE DRIVERS: LEVERAGING SHARING ECONOMY BUSINESS PLATFORM CUSTOMERS DATA FOR ENHANCED VALUE CREATION**

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Relevance of the topic

The topic of value creation on sharing economy business platform is highly important nowadays. Platform businesses have emerged as online marketplaces that enables consumers and suppliers to exchange goods, services, or information. Throughout the past few decades, the business environment has rapidly grown and drastically changed, therefore industries had to adapt even faster in order not to fall behind. As the ecosystem evolved, sharing economy business platforms have emerged as a mean for firms to gain a competitive advantage, sustainable growth, and exploit one of their most valuable assets: customers' data. The more users a firm attracts on its platform, the more data it generates, enabling the optimization of various operations, including process enhancement, product and service improvements, customer satisfaction, and brand reputation. Additionally, this creates value for both stakeholders involved in the platform's environment. Through customer data, companies can determine and predict how the market demand will change, and understand rising consumptions trend, consequently, adapt to rapid changes (Kuusela Hannu, 2014). Given the pace of how things are constantly renewing, it is fundamental to find the solution that enables companies to strengthen their ability to stay relevant, and what makes it easier is relying on and using valuable information such as customers' data. Furthermore, a slightly different concept, connected to value creation, which has been discovered and brought to the attention of firms' management, is value co-creation. In the recent years, offering a valuable service, or an appealing product could not be sufficient to remain competitive in the market. Value co-creation is the generation of value that involve numerous supplier-consumer interactions within the established network (Feng-Shang WU, 2022). Engaging all the participants in the value co-creation framework is a key aspect both for enterprises and customers, as a close collaboration enables the parties involved to gain maximal commercial value. Overall, value creation and users' data is a crucial topic that can have several implications in terms of success and growth.

Exploration of the topic

Value creation and data-driven customers value drivers in business platform have been carefully studied in the past few years, placing particular emphasis on data utilization in order to favor companies to make accurate decisions and model their products to achieve customer satisfaction.

However, there is still a research gap in terms of perceived customer value, which can be used as a measurement scale to test value co-creation results and effectiveness. As Solakis, Pena-Vinces and Lopez-Bonilla,(2022) suggest, given that a result of value co-creation is the value itself that could be determined by the customer. Consequently, value created is always evaluated differently between customers according to each of them unique perception of value. Authors such as Christopher DC. Francisco (2021), Rahikka, Ulkuniemi, and Pekkarinen (2011), given the contemporary situation of constant transition, underlined the relevance of customer satisfaction for the sake of success in the long run.

Novelty of the research

Numerous researchers and the academic community have broad different opinions; therefore, it would be necessary to investigate how and why creating value and data-driven customers value drivers positively affect businesses. Given that industries have become highly competitive, figuring out how to increase the customer retention rate and understanding why customer value perception could be one of the most relevant aspects from a business perspective, would definitely be important. In this context, the master thesis aims to contribute by providing valuable insights into these dynamics.

The aim of the study

The aim of the study is to identify the key data-driven customer value drivers and their impact on the most perceived customer value within sharing economy business platforms among Italian customers.

The problem of the Master thesis

Not always shifting from value creation to co-creation is easy for businesses, customer's attitude may sometimes negatively affect this mechanism, and it may consequently be difficult to determine the most relevant value-drivers due to different expectations rather than exchanging value.

The objective of the Master thesis

The main objectives are:

1. Using academic literature analysis to explore the theoretical framework related to sharing economy business platforms and value co-creation.
2. Establish a research methodology to investigate the relationship between data-driven customer value drivers and the perceived customer value in sharing economy business platforms among Italian customers.
3. Determine and examine the key elements that drive business success in sharing economy business platforms.

Research methods

Scientific literature analysis, questionnaire-based survey, statistical regression analysis, scrutiny of the findings.

Description of the structure

This Master thesis will be structured as follows: literature analysis, data collection and examination and conclusion. In the first part scientific research and theoretical background are collected and presented. The second chapter of the thesis shows the quantitative research methodology employed, hypothesis and the results of the data gathered. The second part will be concluded with a discussion of the results obtained and confirmation or rejection of hypothesis. The final part includes the conclusion and recommendations based on the research.

Usage of artificial intelligence

In line with the methodological guidelines of the University, the author declares the use of artificial intelligence (AI) tools in the preparation of the master thesis. Specifically, AI was used in a limited capacity, mainly for language refinement purposes. This tool, was employed to assist with paraphrasing, improving grammatical clarity, and enhance the overall readability of certain parts of the theoretical section. The academic content, including the literature review, research design, data collection, statistical analysis, interpretation of results, and conclusions, was conducted independently by the author. The usage of AI did not extend to the generation of ideas, arguments, or research findings. All sources included and cited in this thesis were independently identified, accessed, and referenced by the author according to the academic guidelines.

1. THEORETICAL CONCEPT OF BUSINESS PLATFORM AND DATA-DRIVEN CUSTOMER VALUE DRIVERS: A CONCEPTUAL FRAMEWORK OF BUSINESS

Over the past couple of decades, the online ecosystem has played a key role in many aspects of the business world. Digitalization is transforming and challenging growing firms and leading to business model innovations. In response, organizations have had to adapt quickly, leveraging new technologies to get new opportunities and maintain competitive advantage. At the heart of this transformation there is the rise of digital platforms, technological architectures that allow interactions between two or more parties, usually customers and producers.

Table 1. *Business platform definition*

Definition	Authors	Key themes
"Platforms are characterized by their open business models that inherently rely on independent participants to co-create value."	Täuscher, K., & Laudien, S. M. (2018)	Openness, co-creation, decentralization
"We define a platform as a business enabling value-creating interactions between external producers and consumers. The platform provides an open, participative infrastructure for these interactions and sets governance conditions for them."	Penttinen, E., Halme, M., Lyytinen, K., &Myllynen, N. (2018)	External actors, interaction facilitation, governance
"Platforms can be seen as a "market", where users' interactions with each other are subject to network effects and are facilitated by a common platform provided by one or more intermediaries."	Schweiger, A., Nagel, J., Böhm, M., & Krcmar, H. (2016)	Intermediary role, user interaction, network effects

"Platforms are distinct from conventional products in that they have potential to generate positive feedback loop, also called "network effects", between the primary product (the platform) and its users."	Gawer, A., & Cusumano, M. A. (2015)	Network effects, user feedback loops

Source: compiled by the author based on Laudien, S. M. (2018), Myllynen, N. (2018), Krcmar, H. (2016), Cusumano, M. A. (2015).

Despite the different words used, a clear pattern seems to come up across business platform definitions (see Table 1): structured ecosystems that thrive on participation interaction, value co-creation, and scalable infrastructure. These elements form the theoretical conceptual basis for understanding customer data and value generation in platform businesses.

A digital platform is characterized by strong network effect, links between two or more different and interdependent parties and usually drives value-added interactions through the exchange of goods, services, information and/or currencies (Marvin Drewel, 2020). It is important to emphasize that value co-creation is one of the core points when it comes to business platform. These platforms thrive on network effects, trying to increase the traffic, as the traffic itself boosts the value of the platform that increases as more participants join and engage. This mechanism drives innovation and often leads to beneficial dynamics for businesses. "Digital platforms create value in two-sided platforms through a trustworthy environment, data-driven expansions, personalized services, and engagement mechanisms" (Trabucchi, 2022). In this context, value co-creation is not static, but dynamically shaped and modified by customer behavior, platform design, and data analytics. Having effective methods within your ecosystem permits firms to harness customers' data to tailor offers, optimize engagement, therefore personalized experience becomes essential. As such, this paper focuses on data-driven drivers of customer value, investigating how businesses can leverage consumers' data to enhance value co-creation, and drive long-term growth.

Given the conceptual framework of digital platforms and their role in enabling interaction and value creation, it is important to figure out how they grow and sustain their competitive advantage.

Business platforms have emerged as foundational structures in the digital economy, playing an intermediary role that ensures and facilitates interaction among stakeholders. The platforms that are successful have a characteristic in common, they tend to grow very fast and, at the end, only one winner will benefit from the referred market, therefore only one winner remains (Van der Aalst, 2019). Developing a compelling product or service is essential, but what makes the difference in most of the cases is the scalability of the platform, because it often determines the long-term success. Digital platforms benefit from low costs and the ability to reach a global audience very rapidly, investing a relatively modest budget. A well-structured platform is characterized by efficient attraction of customers, but it also fosters participation, where each new user adds value to existing ones, accelerating growth. The online environment often evolves to monopolistic structure due to the cumulative power of network effects, an important factor involved in platform establishment. Once a platform secures a significant portion of users and becomes dominant, late entrants may face serious barriers. Given the importance of dominating the market from the very beginning, this "only one winner remains" dynamic makes the rapid scaling crucial for establishing a sustainable competitive advantage. Attracting a vast customer base also enhances the platform's ability to collect customers' data, which improves decision-making and service optimization. Platforms that can gather accurate data and effectively leverage analytics, are able to improve organization performance, business processes, customer experience, and market enhancement (Elia et al., 2022). As platform usage intensifies, so does the opportunity to refine algorithms, user interfaces, and operational processes, leading to an increasing platform quality. Thus, platform growth and scaling are not only a function of expansion but a strategic process of adding and creating value into the business. Organizations which are capable to leverage customers' data can achieve data-driven optimization, which helps both sustainable growth and differentiated value co-creation.

1.2 Sharing economy platform within the digital ecosystem

Business platforms generally facilitate interactions between producer and consumers, the sharing economy platforms represent a specific subset characterized by peer-to-peer exchanges of assets and services. Unlike traditional e-commerce, where value is often created following a standard workflow from firm to client, the sharing economy mostly relies on a triadic relationship between the platform provider, the peer-provider (such as Vinted, Amazon, Airbnb etc.), and the customer.

Creating shared value can help sharing economy platforms to maintain their sustainable innovation in their ecosystem (Rong et al. 2021). In this context, value is not only delivered but co-created through interaction of resources such as time, knowledge, and often physical assets. These platforms thrive on network effects, where the increasing number of providers directly enhances the perceived value of the customer base. "Sharing economy platform firms create value and gain a competitive advantage by utilizing on demand resource adaptation, big-data-driven network effects, and ecosystem resource coordination” (Zeng, J., Tavalaei, M. M., & Khan, Z. 2021). Because these transactions usually happen between individuals, rather than established and well know brands, trust, transparency, and social interactions become highly important data-driven drivers that potentially mitigate the risk people may perceive. Therefore, for sharing economy platforms, leveraging customer data is not only about operational efficiency, but about building a trustworthy infrastructure that empowers users to act as both consumers and value co-creators.

1.3 Network effects on business platforms

As it has been briefly introduced in the previous paragraph, it is essential to highlight one of the most critical phenomena that enables a platform to thrive: network effects. These effects represent a central mechanism in the success and scalability of business platform. According to Varga, Cholakova, Jansen, Mom and Kok (2023) network effects are a core requirement for a successful platform, especially when it succeeds in bringing together a large amount of customers who tend to interact with others. The more users a platform attracts, the more value can be extracted for each individual. Platforms, in order to take advantage of this mechanism, must therefore be designed to stimulate and facilitate network effects which may bring numerous benefits, especially in the value co-creation process. This effect is potentially very powerful, and can be categorized in two different types, named as “direct” and “indirect” network effects. Direct effects typically occur when platforms attract customers, which consequently bring friends, friends of friends, etc. given the experience they have within the platforms, or the benefit they receive from those, so that the platform adoption grows organically. We talk about “indirect” network effects, which sometimes may be even better than direct, when external parties become interested in the platform after seeing the number of customers they convert (Gawer, A., & Cusumano, M. A. 2014). For instance, external third parties become interested in the platforms because of the results they achieve and the expanding user base.

To summarize, network effects not only contribute to rapid growth, but also deepen the collaborative value generation between platforms and their customers. This makes a fundamental element in designing competitive and sustainable platform businesses.

1.4 Platform business customer data types and measures

After explaining the initial platform's path, it is crucial to point out how actually data enables businesses to shift gear. As digital platform scale and the number of customers increase, data becomes one of the most valuable assets, and simultaneously, one of the most powerful drivers. However, data generation is not a passive process, it must be analyzed and strategically implemented into the platform's architecture. "Data-enabled learning from customer data can enable digital platform competitive advantage and growth, affecting factors like firms' learning functions, data accumulation, and customer beliefs" (Wright, J. 2023). Ideally, effective data generation begins capturing meaningful customer information that are usually classified into several different key types, each contributing to value co-creation in platform businesses, following some of the most relevant data types:

- Behavioral data: the behavioral data most often come in the form of choices, or other easily observable behaviors, (Wilson, R. C., & Collins, A. G. 2019). Behavioral data is composed by time spent on the platform, clicks, significant insight in order to map the customer journey and engagement optimization. This information helps platforms to refine algorithms, predict future demand, and enhance products recommendation to their customers, improving their ability to match efficiency between supply and demand.
- Attitudinal data: refers to the feeling or emotions that a customer has towards the product, brand or customer experience. These data cannot be gathered using passive mechanism being emotions, so the main methods for collecting it are interviews, survey, feedback form.
- Transactional data: data which encompasses financial transactions, order histories, and payment information (Ijomah et al. 2024). These data types are significant in order to evaluate platform liquidity, pricing model, offering insights in terms of revenue generation.
- Identity data: descriptive data which provides information such as name, age, gender, location. Usually used for specific techniques like customer profiling and personalization. While platforms must comply with strict privacy regulations, these data enable segmentation, fraud prevention, and localized strategies.

These are some of the data types that allow online platforms to design a comprehensive picture of each customer, enabling reactive and predictive business strategies through some distinct metrics that will be presented later in the chapter.

"Platform design can motivate user data contribution through mechanism like reciprocity, peer recognition, and self-image, which work differently across motivations states" (Zhu, K. X. 2018).

Moreover, as illustrated by Zhu, engaging platform design could motivate customers to voluntarily contribute with their data.

Additionally, the real value of data can be discovered when businesses convert it into strategic decisions. Firms that are actively able to generate and leverage valuable information such as data, can refine their strategies, optimize resource allocation, and even predict future market needs. In this case, data generation becomes crucial for platform development and a key of both competitive differentiation and sustainable growth. In order to gain information about the business efficiency according to the desired business objectives, activities represented in controlling mechanism are performed, and key performance indicators (KPIs) of business are determined (Pérez-Álvarez, J. M., Maté, A., Gómez-López, M. T., & Trujillo, J. 2018). To fully take advantage of the strategic potential of customer data, companies must quantify the impact through key performance indicators (KPI). These metrics provide critical insights into customer behavior, evaluate network efficiency, and the effectiveness of data-driven initiatives. By analyzing the right set of KPIs, firms can translate raw data into informed actions that increase the overall success of the customer-platform relationship. What follows is a detailed description of some of the main metrics used to gain valuable users' information:

- Churn rate: Churn is defined to be the activity of customers deciding to leave the company and reject the services offered by it due to dissatisfaction and/or due to better products form other suppliers that fall within the customer's budget (Umayaparvathi, V., & Iyakutti, K. 2016), signal of possible platform inefficiency or satisfaction processes.
- Customer lifetime value: it enables companies to segment customers and identifies those who bring the company the largest profit in time (Jasek et al. 2018), useful to measure hypothetical revenue from a single customer over the entire relationship and performance forecasting.
- Engagement metrics: quantify the level of customer activity and participation, which indirectly may influence network stability and platform reputation.
- Conversion rate: defined as the number of visitors who make a purchase directly from a platform as a percentage of total visitors (Di Fatta, D., Patton, D., & Viglia, G. 2018). It indicates how much effectively data is used to move platforms' users from browsing to purchasing.

In the context of platform-based business models, customers' data is a strategic asset that can drive competitive advantage. To better leverage data, platforms must understand what types of customer data they aim to collect and are actually collecting, as well as the metrics through which value can be measured. As platforms operate and gather data on customers' behavior and preferences, they unlock new capabilities to navigate and influence market shapes. By analyzing consumer data, firms can segment their customers precisely, identify trends, and predict future purchasing behavior. This set of activities when implemented correctly (see Figure 1), allows the development of pricing strategies, service recommendations and personalized product, improving value proposition within the customers base.

Figure 1. *Visual framework of platform data collection and utilization*

Source: compiled by the author based on the paragraph's references.

"Big data can enhance co-innovation processes by enabling knowledge creation, driving customer engagement, and impacting service ecosystems" (Ferraris, A. 2021). Strategically, companies that harness those data gain a learning advantage, being able to know their customer more and more; consequently, they become better at serving them, creating a cycle of self-improvement. Furthermore, it helps businesses to self-guard themselves against competitors, as it becomes increasingly difficult for late entrants to replicate, especially for those who lack the historical records and behavioral insights of established platform.

Finally, customers' data is crucial to unlock strategic business value. When used effectively, it allows platforms to offer tailored experiences, optimize operations, and build a defensible market position, grounded in deep customer understanding and data-informed decision-making.

1.5 The concept of customer value and its measures in platform businesses

Customer value has been studied in numerous academic disciplines such as strategic management, psychology, and organizational development. Customer value, perceived quality, and customer satisfaction are closely related, however their concepts appear to be different. Perceived quality reflects user's evaluation of a product or service performance, which in turn influences satisfaction and contributes to the formation of customer value. Thus, customer value can be understood as a construct encompassing functional, emotional, and relational benefits derived from customer-platform interactions (Graf, A., & Maas, P. 2008).

In platform businesses, customer value is no longer passively delivered, with only the firms playing the value creator role, but actively created and co-created. Value is created through mechanism such as personalization, efficient service delivery, and continuous innovation. However, in the contemporary digital age, value co-creation is equally important, as customers are not only recipients, but contributors. The concept of customer value has evolved from resource exchange to resource integration and value in use, emphasizing value generation in customer's specific case becoming increasingly important in markets with high competition (Eggert et al. 2018).

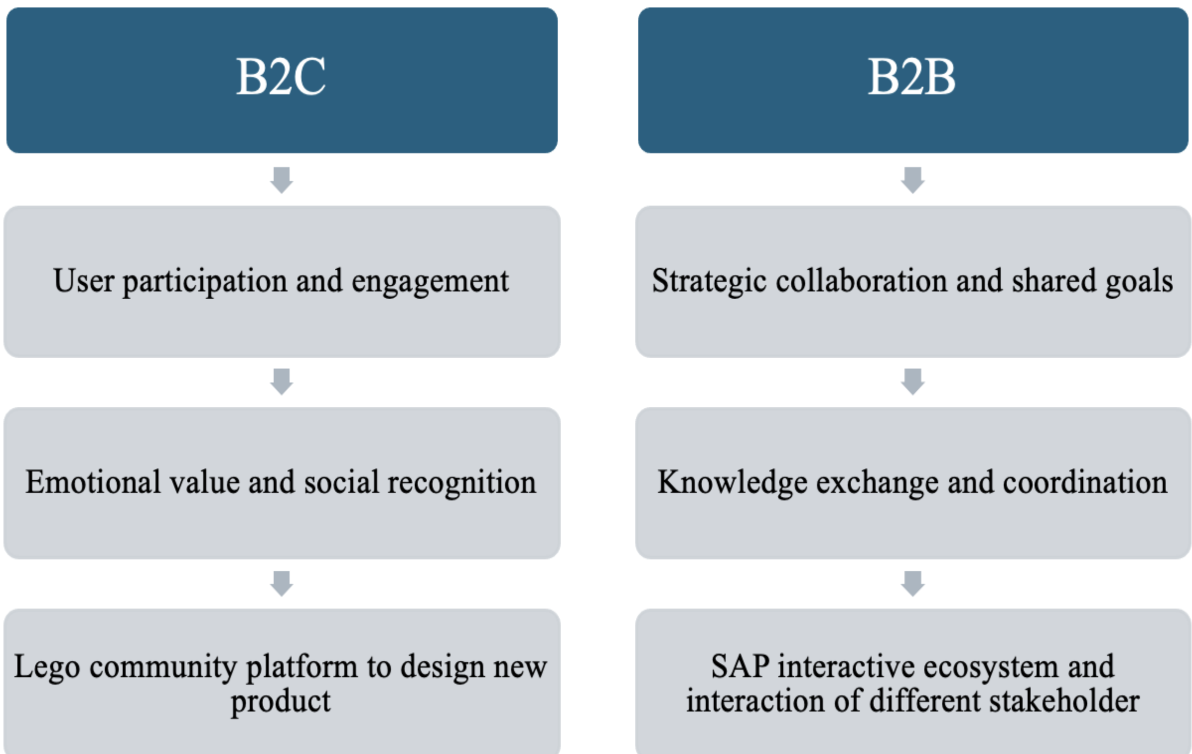
"Through numerous channels, consumers can share their thoughts and opinions as well as resources such as time, knowledge, and skills with businesses, thereby promoting firm performance. This process gives both sides the opportunity to learn and grow" (Feng-Shang Wu, 2022). As described by Feng-Shang Wu, platforms are not only channels for delivering value, but they are also interactive environments that enable and depend on customers' participation to realize their full potential. Customer value can also be also categorized in two different types: outcome value and process value. According to these categories, outcome value refers to the benefit that customers may perceive at the final stage of the service which has used compared to the amount of time, money and effort the customer has spent, while process value represents the positive experience that customers may perceive throughout the process of service interaction compared to the amount of money, time and effort which has been sacrificed (Tran, T. B. H., & Vu, A. D. 2021). We can see the platform as a provider of infrastructure, tools, and rules that facilitates interactions, while customers bring data, feedback, content, inspirations, and in some cases even innovation. This collaborative dynamic enhances product development and network effects. Co-creation "forces" customers to become real partners in shaping their own experiences. In this mutual value-generation model, the line between producer and consumer becomes increasingly tight. Platforms that successfully embrace value co-creation unlock greater innovation capacity. As such, fostering this particular relationship is essential for any business platform seeking sustainable long-term life cycle in the digital economy.

After explaining the value co-creation process, it is important to distinguish two main ecosystems in which this process is carried out, business-to-business platform (B2B) and later in the research introduce the business-to-customer platform (B2C). However, the B2B setting will be discussed solely for context related reason, as the thesis focuses on B2C environments. In business-to-business platform, value co-creation is a strategic and collaborative process that goes beyond transactional efficiencies. B2B platforms gain profit through value creation by integrating customers (which in this case are other entities, not necessarily individuals), partners, and stakeholders in a mutual value co-creation process (Hein et al. 2019). Value is no longer generated in isolation but through collaborative engagement across the environment (see Figure 2). Unlike traditional business models, where value goes from producer to customer, in B2B platform customer value is co-created through strategic collaboration, where clients (organizational customer) contribute with its expertise, feedback and co-design efforts. In this model, platforms play as orchestrators of interaction, connecting numerous parties, around shared goals and results. By enabling shared development, data sharing, platforms grant each participant to benefit from collective intelligence and efficiencies of scale. A notable example of value co-creation in B2B environment is the company SAP. They have developed a platform which brings together SAP and its customers, partners and developers to collaboratively design and test customized software solutions. This solution enables companies to work directly with SAP experts and other stakeholders to co-develop innovations tailored to specific industry needs. For SAP, the process generates valuable customers insights and foster deeper relationships, while participants gain early access to cutting-edge tools to influence product evolution.

The platform itself gains profit not by owning all resources, but by optimizing those co-created processes between the stakeholders involved. More importantly, this model revolutionizes relationships, where trust, transparency, and aligned incentives are crucial. When done correctly and efficiently, the platform becomes a value network, a key player of shared innovation and mutual growth, rather than a simple intermediary.

Looking to the "individuals" customer side, value co-creation mostly refers to customer engagement, emotional connection, and community participants (see Figure 2). Contrary to B2B platform, where collaborations and shared goals are the main purposes, B2C co-creation tends to be more spontaneous and driven by personal motives, such as desire of recognition, self-expression, or belonging. Customers are active players in relational exchanges and co-production, and products carry service potentials that are only realized when people put them to use (D'Andrea et al. 2019). However, this process present unique challenges in B2C system. "While customers are value co-creators during service encounters, they can be value co-destructors as well if they do not play their defined roles" (Zhang, T., Lu, C., Torres, E., & Chen, P. J. 2018). According to Zhang, Lu, Torres and Chen (2018), customers are not only positive stakeholders involved in the co-creation process, often the alignment between customers motivation and company objectives is not easily understandable. Customers may approach co-creation with different expectation such as learning or visibility, while in contrast companies seek for innovation and actionable insights. This misalignment could reduce the effectiveness of co-creation unless clear structures, feedback, and shared outcomes are decided. Despite this barrier, when B2C co-creation is effectively managed, it can be a powerful mechanism. Interactive features within the platform enable users to actively shape products and offerings, while simultaneously adding to the platform diverse perspective. Illustrating a compelling example such as LEGO may help to understand better the B2C mechanism. They have created an open innovation platform that invites customers to design and submit their own LEGO ideas. Community members vote on their favorite concepts, and those that receive enough support are reviewed by LEGO for potential production.

Figure 2. *B2C and B2B business model*



Source: compiled by the author based on Krcmar, H. 2019 and Slongo, L. A. 2019

This explains the concept of value co-creation and defines a company which embraces this specific concept, looking to benefit from the collaboration with its direct customers. To sum up, the effectiveness of B2C co-creation usually depends on the platform's ability to cultivate a reciprocal system that balances customer empowerment with strategic direction, resulting in tangible business outcomes while raising long-term engagement and emotional investment.

1.6 Customers' role in value co-creation and strategic engagement in platform

As it has been discussed above, customers are important stakeholders in the value co-creation process. Customers, in the current business environment, play a far more active and influential role than in traditional linear value chain. Rather than being a passive recipient of value, customers contribute directly to its generation by shaping demand and providing data. Their actions influence many aspects such as product development and overall user experience. "Customers define their need before engaging a solution provider to guide the solution process and identify variables that enable value co-creation" (Petri, J., & Jacob, F. 2016), emphasizing their proactive role in the early stages of value formation. Additionally, customers play various roles and contribute various resources to the co-creation of value with businesses, enabling them to be more effectively and efficiently served (Agrawal, A. K., & Rahman, Z. 2015), underlining the multifaced nature of their participation. As such, understanding and enabling customer participation across all phases of the value co-creation process is essential for sustaining innovation and competitive differentiation in digital ecosystem.

As described, it is essential for platform-based businesses to make customers feel actively involved in product development and innovation processes. Psychological empowerment, connection and user satisfaction positively influence online brand community participation, leading to increased consumer involvement in brand value co-creation (Hsieh, S. H., Lee, C. T., & Tseng, T. H. 2022). By enabling users to tailor their experiences, and influence service delivery, platforms can foster a greater sense of involvement and personal relevance, consequently increasing the psychological empowerment. However, alongside these opportunities, challenges related to trust have become significantly important in platform-user interactions, especially due to the recent scandals related to pillars of this business sector such as LinkedIn or Facebook data breaches. The growing societal concern over personal data privacy and digital safety has shifted public expectations towards transparent practice. Therefore, platforms must establish effective governance models that aim to protect customers' rights while still enabling system optimization and innovation. "Platforms should be required to make official disclosures about their privacy-related policies and practices, balancing user privacy with platform optimization, to better integrate them in current regulatory framework" (Van Hoboken, J., & Fathaigh, R. Ó. 2021). Platforms firms rely on customers insights to provide value. Trust is a key aspect between the above illustrated interactions. Effective regulation can protect user and ensure that platforms operate considering not only profitability and business development, but beneficial societal factors as well.

In the same circumstances, service quality has been recognized as a determinant of customer value in digital business platform. Recent studies emphasize how customers tend to evaluate service quality through numerous dimensions such as information quality, system quality, delivery performance, problem resolution and ease of use. As described by Kang and Namkung (2024), clear and reliable information, intuitive interfaces, and product descriptions enhance customers' perception of the platform's value. Similarly, Jiang, Jun, and Yang (2016) argue that service quality characteristics such as responsiveness, reliability, assurance, may significantly affect and predict customer perceived value in online platforms. Therefore, service quality functions appear to be data-driven drivers of value as each determinant can be monitored and improved through customers data. When a platform keeps the service quality at a relevant level and it performs consistently and addresses customers' needs, those tend to perceive a higher overall value of the platform, thus service quality represents an operational mechanism through which digital platform raise the value co-created with customers.

To sustain the mechanism, platforms tend to depend on various strategies which can be systematized as follows: technological, social, emotional and interactive.

Technological methods aim to personalize the user experience. "Technological strategy refers to personalization, which can increase the number of customers receiving personalized experiences when real-time touchpoints are linked to a customer master data management system that integrates identity, contactability and traceability data" (Valdez Mendia, J. M., & Flores-Cuautle, J. D. J. A. 2022). Similarly, gamification principles, such as social interaction and sense of control, encourage hope, leading to increased customer engagement and digital sales, instead of compulsion (Eisingerich et al. 2019). These techniques make use of automation and data to provide seamless and relevant digital customer journey.

The social strategy approach emphasizes community dynamics and peer interaction. Platforms that encourage sharing, discussion, reviews, and collaborative behavior often have greater advancement. For example, in the context of social commerce platform, engagement is influenced by social interaction and motivational drivers, with interpersonal dynamics and perceived value playing a pivotal role (Busalim, A. H., & Ghabban, F. 2021). As Carlson, Gudergan, Gelhard and Rahman (2019) explain, "engagement level on business platform can be enhanced when aligned with customer knowledge and avant-gardism, underlining the importance of tailoring social features to user behaviors".

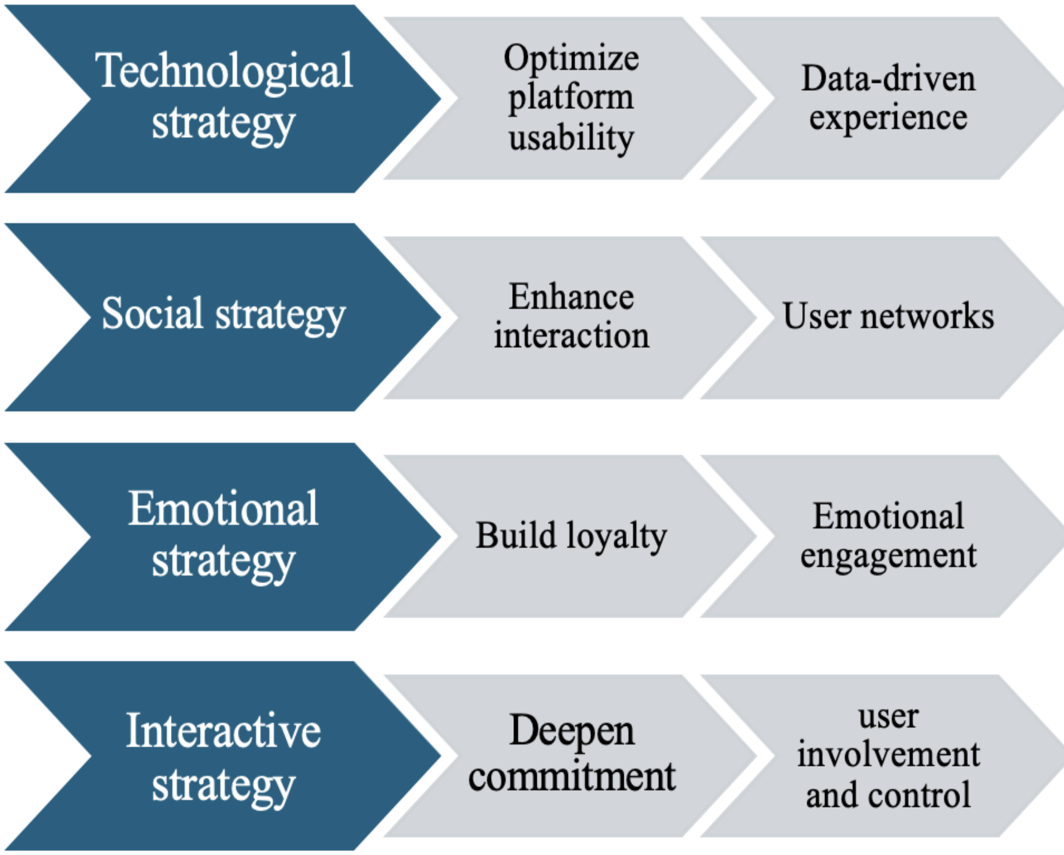
Looking at emotional strategies, platforms also target emotional aspects to deepen brand attachment and consumer loyalty. "Customer engagement and brand image positively influence purchase behavior, with pleasant and arousing experiences on engagement platforms leading to increased brand loyalty" (Blasco-Arcas, L., Hernandez-Ortega, B. I., & Jimenez-Martinez, J. 2016).

As just described, pleasant experiences positively affect purchase behavior and customer loyalty. By touching emotional factors, platforms increase user satisfaction and repeated interaction.

Finally, interactive strategies aim to create specific environments where customers feel involved and influential. The Apple store as a DIP (digitalized interactive platforms) is configured for ordinary people, concentrating mostly on customer experience and not on the predominant practice of appealing information about the features of products, strategy typically adopted by many technology companies (Roy et al. 2023). In this case, the focus is on customer experience rather than product functionalities. Apple has developed an interactive environment which allows a continuous feedback loop between customer and the platform, creating a lock-in effect through transparent interaction.

Taken together, these strategies (see Figure 3) highlight that customers' motivations are not only functional, but they are also effective, social, and experiential. Platforms, when succeed in balancing these different dimensions are more likely to achieve sustainable user relationship that can be turned into higher revenue and competitive advantage.

Figure 3. Customer engagement strategies



Source: compiled by the author based on (J. D. J. A. 2022), Dong, L. (2019) Ghabban, F. (2021), Rahman, M. M. (2019), Jimenez-Martinez, J. (2016), Coussement, K. (2023).

1.7 The moderating role of customer age in sharing economy platforms

Customers' age in the online context can shape perception and decision making. Age can be considered as a relevant moderator variable in this thesis as customers from different age groups do not evaluate online experiences in the same way. Age-related differences in consumer perceptions have been linked to physical and psychological aging processes as well as different life experiences, which influence decision-making and information processing. In the online environment, younger and older customers may rely on different factors when evaluating platform features, since younger customers tend to search for more information and give much more importance to the service characteristics, while older customers may rely more on simple decisions and prior experience (Fang et al. 2016). The role of age as a moderator is also supported with existing research showing how age influences the importance that customers assign to platforms' functionality or usability, and that age moderates the effect of perceived value on behavioral intensions in online business platform contexts (Molinillo, S. 2021). According to previous academic articles, in the online sharing economy business platforms, age may potentially change the strength of the relationship between data-driven customer value drivers and perceived customers value.

1.8 Previous research on the relationship between customer value drivers and customer value

Existing research emphasizes the increased strategic need for recognizing and understanding the key customer value drivers in digital platforms' contexts. Multiple studies have tried to empirically evaluate how specific factors, such as personalization, trust, and interactivity, tend to influence customers' perception of value. While there is a general agreement that these drivers have a positive impact on customer, the scope, methods, and comparative strength of these impacts differ between studies and platform scenarios.

For instance, personalization has been acknowledged as a fundamental value generator, especially in content platforms and e-commerce. Real-time tailored experiences improve relevance, which increases perceived customer value, according to Valdez Mendina and Flores-Cautle (2022). Similar to this concept, Eisingeric, Marchand, Fritze and Dong (2019) show how gamified customization tools, adaptive product suggestions and enhanced interfaces, may create a more interesting and fulfilling experience, which in turn can result in increased customers' loyalty.

Another commonly studied driver is trust, particularly when discussing data sharing and algorithmic openness. In accordance to previous scientific research, platforms' perceived value tends to increase when they set explicit privacy policies and grant customers control over their data (Van Hoboken, J., & Fathaigh, R. Ó. 2021). In this circumstance, trust not only has a direct impact, but it also mediates the relationship between value perception and technology design, allowing platforms to transform ethical practices into competitive advantage.

Emotional engagement has received growing attention as a driver that affects long-term platform attachment and brand loyalty. Research by Blasco-Arcas, Hernandez-Ortega and Jimenez-Martinez (2016), suggests that emotionally resonant experiences through narrative branding, community interaction, or appealing design, usually generate higher phycological value that goes beyond functional usefulness. Similarly, social interaction such as reviews and collaborative environment within the platform, have been found to enhance customers' perception, consequently increasing perceived value.

Interactivity, precisely the ability to encourage feedback loop and co-create content, also plays an important role. Platforms like Apple, illustrate how interactive design and processes foster user commitment and perceived value (Roy et al. 2023). As discussed in the study, the dynamic of value creation has shifted towards value co-creation rather than being supplied by only one player.

Despite these recurring citations, several limitations in the literature remain. First, many researches concentrate on single value drivers without considering the interactions among them.

Second, comparable evaluations across platform types or user categories are frequently absent. Lastly, not many studies try to measure the combined impact of different variables on perceived customer value, although the qualitative definition has been discovered. A thorough basis for the subsequent empirical analysis is established by this review.

The thesis aims to add to this studies by empirically testing the combined effect of some chosen value drivers (personalization, trust, service quality, interactivity) in platform settings.

2. RESEARCH METHODOLOGY AND DATA ANALYSIS

This chapter delineates the methodology employed in the master thesis. It represents the purpose of the study, research design and model, formulation of research hypotheses, which will serve as a foundation to carry out the investigation, instrument utilized to gather and analyze the data, and ultimately the limitations encountered while elaborating the research.

2.1 Purpose of the study

The purpose of this research is to examine and determine the relationship between data-driven user's value drivers and the perceived customer value in platform businesses. As assessed in the literature review, some determinants have been discussed, placing particular emphasis on the impact that each of them has on the customer base. The study aims to identify and evaluate the key factors that can potentially optimize the connection between users and platforms. According to Saarijärvi (2020), personalization positively impacts customer experience and loyalty. Moreover, Wang, Chih and Hsu (2020) confidently point out that interactivity influences users' attitudes towards the platform. Therefore, the author of this thesis analyzes how data-driven value drivers such as personalization, service quality, trust, transparency, interactivity, and social interaction positively influence customer's perception and their interactive behavior within the platform's environment. The research focuses on the Italian market, in order to capture the cultural nuances of value perception within the country.

The main research question that the author would like to address is:

What customer value drivers and to what extent impact perceived customer value in digital business platform?

The objectives are:

1. To determine the impact of the identified determinants (personalization, service quality, trust, transparency, interactivity, and social interaction) on perceived customers value.
2. To explore the moderating effects such as user age on the relationship between determinants and customer perceived value.
3. To provide useful insights and recommendations to platform businesses' leaders on how to potentially enhance customer value creation through strategic improvements.

The dependent variable that was used in the research is the customer perceived value (measured in a 5-point Likert scale).

In terms of independent variables: personalization, trust, service quality, interactivity, gamification, social interaction (measured in a 5-point Likert scale).

Customers age was used as moderator variable (measured in ratio scale).

2.2 Research hypotheses

After a thorough analysis of the literature review, it is possible to state that customer value drivers play a pivotal role within the online ecosystem, influencing consumer's perceived value in the platform environment (see Figure 4). Therefore, the following hypotheses have been considered meaningful to the purpose of the study:

As discussed in the previous paragraphs, personalized recommendations or experiences while using an online business platform, seem to improve the value customers perceived from the platform. Xu, Luo, Carroll and Rosson (2011) in their study support this theory by showing how the results of personalization in business platforms increase the value that customers perceived through the platform. Thus, the following hypothesis has been developed:

Hypothesis 1 (H1): personalization positively influences perceived customer value.

According to the literature review, has been emphasized how customers' trust towards the platforms they usually use has a positive influence on the value they perceived from them. Research by Alshibly (2015) supports this theory, stating that online trust appears to be a relevant element in order to improve customers perceived value. Therefore, the following hypothesis has been developed:

Hypothesis 2 (H2): platform's trust positively influences perceived customer value.

Another important factor discussed in the literature review which affect customer perceived is service quality. Studies developed by Kang and Namkung (2024) and Jiang, Jun and Yang (2016), point out that service quality factors such as ease of use and information quality seem to have a positive impact on customers perceived value, thus the following hypothesis has been developed:

Hypothesis 3 (H3): service quality positively influences perceived customer value.

Furthermore, Wu (1999) and Roy, Singh, Sadeque, Harrigan and Coussement (2023) have indicated how platform interactivity positively affects the perceived value a customer has towards the platform, thus the following hypothesis appears to be relevant to the thesis' objective:

Hypothesis 4 (H4): platform interactivity positively influences perceived customer value.

Eisingerich, Marchand, Fritze and Dong (2019) and Jia and Yu (2025) have analyzed how gamified mechanics can be a vehicle to create and enhance customers value. By establishing an efficient solution for customers' needs, the perception to the platform tends to increase. Consequently, the following hypothesis has been developed:

Hypothesis 5 (H5): gamification positively influences perceived customer value.

Ngo (2025) has identified that social interaction such as reviews and comments shared by other customers significantly shape the perception of other customers who will interact with the defined product or service offered by the online platform in question. It has appeared that this directly enhance the perceived value customers attach to the product or service which has reviews or comments, therefore the following hypothesis seems to be relevant to the research:

Hypothesis 6 (H6): social interaction features positively influences perceived customer value.

To fully understand the relationship between customers perceived value and the main customer data-driven value drivers a moderator variable, customer age, is introduced. This analysis is critical for unraveling trends across diverse generations. Santos (2024) highlights how younger generation tends to value more online experiences rather than older generation, as younger people are usually more involved in the online world. Furthermore, Molinillo (2021) shows how age is a common characteristic which influence customers perceived value, especially in the online business platforms context, as age moderates the importance given to the social interaction present on these, providing relevant insights to validate the hypothesis that customer age moderates the relationship between different determinants (H7 – H12) and customer perceived value in the context of online business platform.

Hypothesis 7 (H7): customer age moderates the relationship between personalization and customer perceived value

Hypothesis 8 (H8): customer age moderates the relationship between platform's trust and customer perceived value

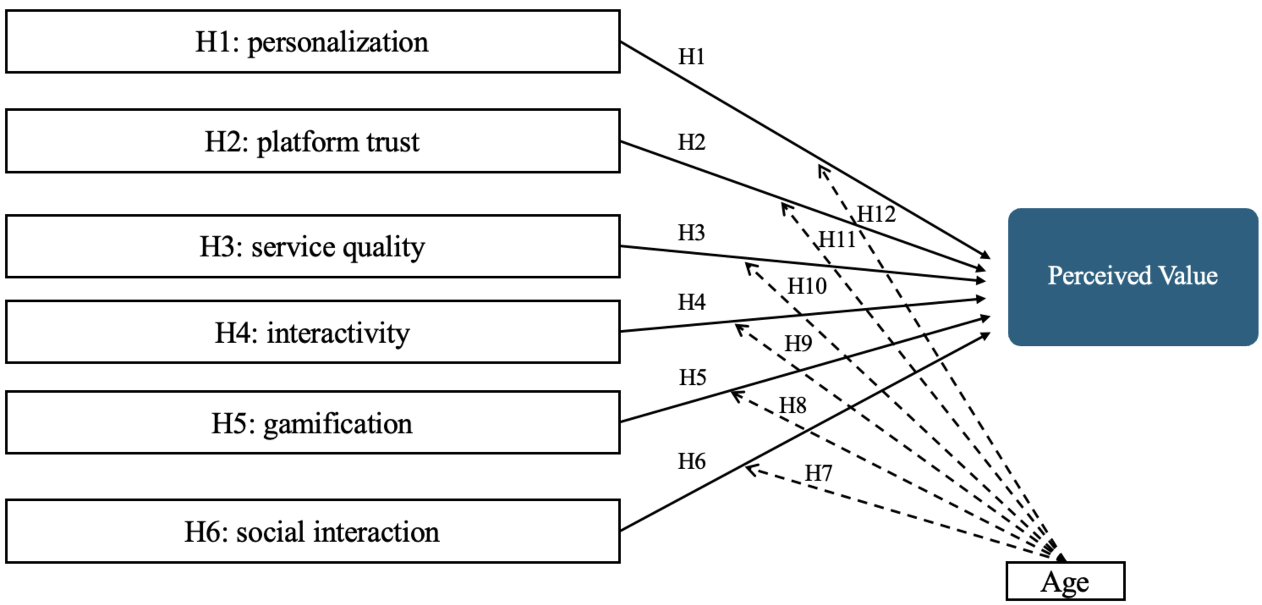
Hypothesis 9 (H9): customer age moderates the relationship between service quality and customer perceived value

Hypothesis 10 (H10): customer age moderates the relationship between interactivity and customer perceived value

Hypothesis 11 (H11): customer age moderates the relationship between gamification and customer perceived value

Hypothesis 12 (H12): customer age moderates the relationship between social interaction and customer perceived value

Figure 4. *Impact of value drivers on perceived value*



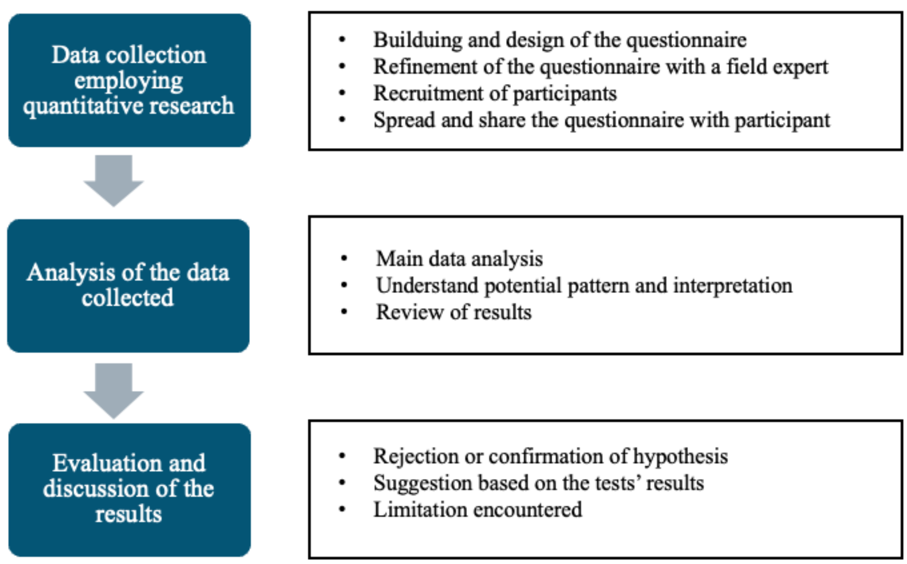
Source: compiled by the author based on the research methodology

These hypotheses aim to explore further the relationship between sharing economy business platform and customers' perceived value.

2.3 Research design

To examine these relationships, quantitative research was adopted to gather and analyze data from a sample of business platform customers. This approach enables the systematic examination of the relationship between perceived customers value and the determinants of the value drivers. The data collection employed in this research is a questionnaire-based survey (in English and Italian language) (see Appendix 1). In accordance with Ong (2012), a questionnaire is a data collection tool and is vital to the credibility of the research project. To ensure data relevance, the target population is defined as Italian customers who use to purchase on sharing economy business platforms. This geographic and sectoral focus allows to perform a controlled analysis of selected value drivers. A structured online questionnaire will be spread to participants, in this case customers, who have purchased at least one product or service over the past three months on a sharing economy business platform (filtering question). The questionnaire was distributed to customers through the author's personal social media channels (LinkedIn, Instagram, Facebook), including relatives, friends, and via email to colleagues. To comply with the individuals' data regulations, participants were ensured about anonymity and confidentiality. The sample did not have strict requirements that have to be met by participants in terms of age, gender, or other similar factors.

Figure 5. *Research plan*



Source: compiled by the author

2.4 Data collection method and measurement scales

A questionnaire is the tool employed in this thesis to gather primary data that allowed the researcher to test the hypothesis. The structure of the questionnaire is as follow: a short introduction welcomed the respondents when they open the link to fill in the questionnaire, as well as a summary about the author, field of the study, and the aim of the research. Additionally, the introduction is intended to create an "emotional connection" between the respondents and the author, helping respondents feel valued, which may lead to higher data quality.

1. The control question was used to verify whether the respondent targeted has purchased on an online business platform a product or service over the past 3 months. Respondents indicating a negative response to the aforementioned question in the survey were considered ineligible to the study analysis, therefore they would be excluded to further research. This question helped to screen the respondents who decided to participate in the analysis of the research objectives, in order to gather relevant data, a negative answer to the initial question would automatically consider the person not suitable for the test.
2. The construct of personalization has been adapted from the questionnaire used by Xu, Luo, Carroll and Rosson (2011) in their research. The construct has three statements designed to evaluate the customers' perceived value through personalization. In the researchers' study, statements such as "I feel the personalized recommendations on the platform increases the value I get from the usage of it", "Personalized offers help me to find what I need in a more efficient way", and "The platform's ability to adapt to my preferences makes it more valuable" have been designed. Responses were recorder on a 5-points Likert scale, ranging from 1 to 5, with 1 "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and 5 for "strongly agree". High scores on the scale represent high levels of customers agreement with the statements. In this research questions in regard to personalization have Cronbach's $\alpha = 0.850$
3. The construct of interactivity has been adapted from the construct used by Wu (1999) in his article. In order to test interactivity, in the researcher's study, statements as: "The ability to give feedback or interact with the platform (through emails or feedback form) increases its value to me", "When the platform quickly responds to my input, I feel it adds value", and finally "I find platforms more valuable when they allow me to shape my experience" have been designed. Responses were recorder using a 5-points Likert scale, ranging from 1 to 5, with 1 equal to "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and finally 5 for "strongly agree". High scores on the scale represent high level of customer agreement with the statements given. In this research questions in regard to interactivity have Cronbach's $\alpha = 0.870$
4. The assessment of Gamification has been adapted from the survey implemented in (Jia, F., & Yu, J. 2025) research. The construct has three statements designed to evaluate gamification on business platform: "The use of the gamification on e-commerce platforms improves the value I perceive of it", "Gamification, when present in business platform, makes me feel pleasant", and lastly "Playing games on e-commerce platforms allow me to

obtain useful information for more cost-effective shopping, therefore higher perceived value". Responses were recorder using a 5-points Likert scale, ranging from 1 to 5, with 1 indicating "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and 5 for "strongly agree". Higher scores on the scale correspond to elevated level of customers' agreement. In this study gamification questions have Cronbach's α = 0.881

5. The assessment of service quality has been adapted from Kang and Namkung (2024), where in the research they designed the construct as follow: "The product information on the online platforms are usually easy to understand", "I can search for items that I need quickly on the online platforms I use", and "The platforms solve the problems I encounter while purchasing a product quickly". The responses were recorder using a 5-points likert scale, ranging from 1 to 5, with 1 standing for "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and finally 5 for "strongly agree". Higher scores on the scale correspond to elevated level of customers' agreement. In this research service quality questions have Cronbach's α = 0.833.
6. The assessment of social interaction, more specifically other customers' reviews or comments, has been adapted from Ngo (2025). In order to test the relationship between social interaction and perceived customers value, the authors have designed the following statement: "Online customer reviews are a valuable tool for online shopping", "Online customer reviews and comments regarding products provide helpful information", "The online customer reviews system contribute to increase the value I perceive of the platform". Responses were recorded using a 5-points Likert scale, ranging from 1 to 5, with 1 standing for "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and 5 for "strongly agree". Higher scores on the scale correspond to elevated level of customers' agreement. In this article, social interaction such as customers' reviews and comments questions have a Cronbach's α = 0.872.
7. The assessment of trust has been adapted from Alshibly (2015). In order to test the relationship between trust and perceived customers value on sharing economy business platform, Alshibly designed the following statements: "The online platforms where I usually purchase products give me the impression that they keep promises", "I believe online platforms tend to have my best interests in mind", and finally "the online platform are trustworthy". Responses were recorder using a 5-points Likert scale, ranging from 1 to 5, with 1 standing for "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and 5 for "strongly agree". High scores on the scale correspond to elevated level of customers'

agreement with the statements. In the research, platform trust questions have a Cronbach's $\alpha = 0.780$.

8. The assessment of customer perceived value has been adapted from Jiang, Jun and Yang (2016), In order to test the relationship of customer perceived value, Jaing designed the following statements: "Compared to traditional businesses, sharing economy business platforms offer attractive product costs", "Compared to traditional businesses, sharing economy business platforms charge me fairly for similar products/services", and "Compared to traditional businesses, sharing economy business platforms provide me more free services". Responses were recorder using a 5-points Likert scale, ranging from 1 to 5, with 1 standing for "strongly disagree", 2 for "disagree", 3 for "neutral", 4 for "agree", and 5 for "strongly agree". High scores on the scale correspond to elevated level of customers' agreement with the statements. In the research, customer perceived value has a Cronbach's $\alpha = 0.800$.
9. Demographic questions are presented after each hypothesis were tested in the final part of the questionnaire. Demographic questions are useful information mostly used to describe the sample and determine whether the individuals recruited represent the recipient the author wants to assess within the research (Hughes, J. L., Camden, A. A., & Yangchen2016). In this research five demographic factors are considered significant: the respondent's location, age, gender, monthly income (after taxes) and level of education. The respondents' location was measured using a nominal scale, while their level of education, age, and monthly income were measured using an ordinal scale.

Pilot study. In order to refine the questionnaire, assess the effectiveness of the implemented questions and evaluate the quality of procedures and methods of the questionnaire, the pilot study has been conducted inviting 4 respondents to complete the questionnaire, followed by a face-to-face interview for discussion. The data gathered in the pilot study has been used to improve the wording of 6 statements which appeared not clear due to the translation from English to Italian, the changes made are the following:

1. In the personalization construct the statement was changed from "Sento che le raccomandazioni personalizzate sulla piattaforma aumentino il valore che ne ottengo dal suo utilizzo" to "Le raccomandazioni personalizzate che le piattaforme suggeriscono aumentano il valore che ottengo dall'utilizzo".

2. In the interaction construct one statement was changed from “Trovo le piattaforme più preziose quando mi permettono di modellare la mia esperienza” to “Trovo che le piattaforme siano migliori quando mi permettono di modellare la mia esperienza”.
3. In the gamification construct two statements were changed from “L’uso della gamificazione sulle piattaforme di e-commerce migliora il valore che percepisco da esse” and “La gamificazione, quando presente in una piattaforma online, mi fa sentire a mio agio” to “La possibilità di giocare e ottenere sconti o premi sulla piattaforma aumenta il valore che percepisco di essa” and “La presenza di giochi, quando presenti sulle piattaforme, mi fanno provare sensazioni positive”.
4. In the trust construct one statement was changed from “Credo che le piattaforme online tendano ad avere a cuore I miei migliori interessi” to “Credo che le piattaforme online tendano a tenere a mente I miei migliori interessi”.
5. In the social interaction construct one statement was changed from “Le recensioni dei clienti online sono uno strumento prezioso per gli acquisti online” to “Le recensioni dei clienti online sono uno strumento utile per gli acquisti online”.

The Italian questionnaire is presented in Annex 2. The data gathered while completing the pilot study were not used for further research.

Additionally, a business expert’s insight about the questionnaire and hypotheses relevance has been obtained. The Head of Customer Loan from a well-known company operating in the Lithuanian market, InBank, which has an established online platform, was interviewed. The main highlights arose from the interview are described:

- **Personalization** in business platform is a valuable tool, even when present with simple features. Sometimes it is hard to determine the best moment or find the best customer who “needs” a personalized experience or offer. Usually companies may fail at finding the best moment or feature, however it is a relevant and useful tool which is widely used.
- **Interactivity** generally brings value to customers, although different preferences have to be easily and quickly accessible to the customers, and smoothly respond to customers’ input.
- Customers often interact very well with **gamification** items and these are extensively used on business platform for various reasons (to give customers discounts, collect survey responses, product reviews, leads). Gamification will probably never go out of trend or lose its relevance

to platform businesses, as it also triggers human behavior. For customers, it is hard to resist the urge to test their "luck", and for firms is a secure source of fresh data.

- Platform **trust** is very important, but trust can also be built as an impression. Therefore, more educated customers may be careful about using a platform which they have never heard about, while some other groups may just trust the first impression. It is vital to constantly work on platform trust, as this enhances customers perceived value, consequently increasing the number of customers converted.
  At InBank for example, trust is a sort of issue, according to the data and market research new customers tend not to trust the company, compared to loyal customers who have already used or purchased our products or services, she reported.
- When there are not enough information, or poor service quality on the platform, this can very easily cause a massive customer drop off. **Service quality** is paramount for every platform and it is a basic starting point on which the business should be built on. Internal analysis shows how service quality positively affects customers perceived value. Additionally, sometimes even competitor analysis overview is run in order to test and understand how the business is positioned within the market in terms of service quality.
- Finally, **social interactions** are fundamental, especially it those are not positive. Generally, all big players in the market are extremely careful about what people thinks about them. There are various methods on how to build different system in order to increase and collect positive reviews about the products offered. The impression that other customers have tried something before actually purchasing it, directly increase the customers value perceive. At InBank public reviews are the most important, they also have set up an internal algorithm which "push" people to leave reviews after interacting with what we offer, she reported.

Questionnaire distribution. The questionnaire was prepared on google forms and it was conducted from 16th of March 2026 until 7th of April 2026. The respondents were approached through different social media channels such as Facebook, Instagram, LinkedIn. All respondents were informed about the purpose and the duration of the research before starting the actual survey. Furthermore, all respondents were ensured about anonymity and confidentiality. There was no time limit to complete the survey. The questionnaire was conducted both in English and Italian language.

Sampling method. In this thesis, the participant criteria are not tightly defined, with no strict requirements in terms of age, gender, or other similar factor. The key consideration behind each respondents involved in the research, is that he/she must have purchased a product or service from an online business platform over the last three months. The respondents were chosen using a non-probability convenience sampling method, a widely adopted approach in academic research for its efficiency in terms of time and cost savings.

The survey sample. In recent literature, multiple approaches have been suggested in order to consider the sample size adequate to the research instrument. Memon, Ting, Cheah, Thurasamy, Chuah and Cham (2020) advice that researchers should determine the sample size through the method called “sample-to-item ratio”, which states that the ratio should be equal to minimum 10 respondents per items (questions). Based on this 10:1 ratio, the study has a minimum sample requirement of 21 statements multiplied by 10 respondents, resulting in no less than 210 respondents. At the end of the questionnaire distribution, 242 responses were collected, however only 227 have been considered eligible for further research, as 15 participants had negatively answered to the initial filtering question, leading to their exclusion to this research.

2.5 Overview of the respondents

In this section the data from a sample of 227 respondents is presented. The demographic characteristics of the participant of this research are presented in Table 2. Based on the data collected, the distribution of respondents by gender is 55% women, 44.6% men and 0.4% other. Regarding the age distribution, participants were asked to indicate their age, and consequently had been grouped into 4 different categories: young adults 18 – 24 years old, early adults 25 – 30, adults 31 – 39 years old, and finally middle-aged over 40 years old. Majority of the respondents fall within the 25 – 30 years old bracket (36%), followed by 18 – 24 (24%), indicating a relatively young participants.

Table 2. *Demographic characteristics of survey respondents*

Demographic characteristics	Frequency	Percentage (%)
Gender		
Male	103	45,4%
Female	123	54,2%
Other	1	0,4%
Age		
18 – 24 years old	47	20,7%

25 – 30 years old	81	35,7%
30 – 39 years old	44	19,4%
40+ years old	55	24,2%
Education		
Other	22	9,7%
High school diploma	65	28,6%
Bachelor degree	69	30,4%
Master degree	59	26%
PhD	12	5,3%
Personal monthly income (after taxes)		
Less than 600 eur	39	17,2%
601 – 1000 eur	22	9,7%
1001 – 1500 eur	50	22%
1501 – 2000 eur	62	27,3%
Over 2000 eur	54	23,8%
Location (area of residence)		
City	161	70,9%
Town	50	22%
Suburb	12	5,3%
Rural area	4	1,8%

Source: compiled by the author based on the results of the quantitative research

In terms of education, who completed high school (29%), bachelor's degree (30%) and master's degree (26%) are almost equally distributed, with fewer people holding a PhD (5%9 or other (10%) education degree. The data presented a varied financial situations in terms of personal income after taxes, with a significant portion earning more than 1000 Euro: 1001 – 1500 (22%), 1501 – 2000 (27%), and over 2000 Euro (24%). These results allow a thorough review of the demographic characteristics of the study participants and provide insightful background information.

2.6 Customer survey data analysis

2.6.1 Reliability and validity

To evaluate internal consistency of the questions items, Cronbach's Alpha was calculated. The Cronbach's Alpha was developed to measure the internal consistency of a scale. Internal consistency reveals to which extent the items included in a test measure the same factor, and it should be determined before the actual test can be used for research purposes to ensure validity of the analysis carried out. The more the items are correlated to each, the more Cronbach's Alpha's value increase (Tavakol, M., & Dennick, R. 2011). The range between a Cronbach's Alpha goes is between 0 and 1, with a value equal or greater to 0.6 being considered good for research, but it is often desired to have a minimum value of at least 0.7 or higher. An Alpha value close to 0 indicates that the items chosen are independent of one another, while results near to 1 indicates strong items correlation.

The Cronbach's Alpha coefficient was calculated using SPSS software for a questionnaire with 21 items, each using a 5-points Likert Scale. The coefficient calculated, had a value 0,926 indicating strong internal consistency (see Table 3). Additionally, considering the multidimensional structure of the survey, Cronbach's Alpha was calculated for each construct present in the research. This approached allowed to examine the internal consistency reliability within each subscale in an easier manner and better comprehensive evaluation.

Table 3. *Reliability statistics, Cronbach's Alpha*

Construct	Cronbach's Alpha	Number of Items
Full construct	0.926	21
Personalization	0.872	3
Interactivity	0.699	3
Trust	0.796	3
Gamification	0.865	3
Service quality	0.807	3
Social interaction	0.796	3
Perceived value	0.868	3

Source: compiled by the author based on the results of the quantitative research

Before proceeding with the actual statistical analysis, the dataset was evaluated for distribution normality, using the Kolmogorov-Smirnov and Shapiro-Wilk tests (reported in Table 4). Each questionnaire construct was considered as a single determinant. According to the 95% confidence level test, the data for all seven analyzed variable scales did not meet the criteria for normal distribution ($p < 0.05$), indicating a non-parametric distribution.

Table 4. *Results of normal distribution analysis*

Determinant	Kolmogorov-Smirnov	*p*	Shapiro-Wilk	*p*
Personalization	0,223	< 0,001	0,840	< 0,001
Interactivity	0,195	< 0,001	0,837	< 0,001
Trust	0,176	< 0,001	0,892	< 0,001
Gamification	0,097	< 0,001	0,966	< 0,001
Service quality	0,189	< 0,001	0,843	< 0,001
Social interaction	0,229	< 0,001	0,801	< 0,001
Perceived value	0,140	< 0,001	0,902	< 0,001

Source: compiled by the author based on the results of the quantitative research

2.6.2 Descriptive statistics of research data

Descriptive statistics were used to investigate the relationship between personalization, interactivity, platform trust, gamification, service quality, social interaction, and perceived value. These included minimum, maximum, averages, standards deviations, and variances value of the research determinants (see Table 5).

Table 5. *Statistical indicators of measured determinants*

Determinant	Minimum	Maximum	Mean	Standard deviation	Variance
Personalization	1	5	3,91	0,987	0,974
Interactivity	1	5	4,15	0,706	0,499
Trust	1	5	3,93	0,826	0,682
Gamification	1	5	2,92	1,082	1,171

Service quality	1	5	4,07	0,779	0,607
Social interaction	1	5	4,17	0,719	0,518
Perceived value	1	5	3,97	0,916	0,839

Source: compiled by the author based on the results of the quantitative research

To assess whether the research determinants are related to each other, Spearman correlation was tested (see Table 6 and Annex 5). Significant statistical relationships were found among all variables.

Table 6. *Correlation coefficients of research determinants*

Determinant	1	2	3	4	5	6	7
1 Personalization	-						
2 Interactivity	0,484***	-					
3 Trust	0,601***	0,534***	-				
4 Gamification	0,396***	0,253***	0,425***	-			
5 Service quality	0,541***	0,599***	0,672***	0,323***	-		
6 Social interaction	0,308***	0,549***	0,369***	0,161*	0,567***	-	
7 Perceived value	0,570***	0,530***	0,726***	0,405***	0,722***	0,415***	-

Source: compiled by the author based on the results of the quantitative research

2.6.3 Impact of data-driven value drivers on customer perceived value analysis

This chapter shows test of the relationship between customer perceived value and data-driven value drivers determinants. The chapter utilizes pairwise relationship, conceptual model and test the hypothesis introduced earlier.

Initially, pairwise relationships were tested between each data-driven value driver and customer perceived value (see Table 7 and Annex 6). All the relationships were statistically significant and other measures appropriate for correct analysis. The Anova F test confirmed suitability of the data for regression analysis and the Durbin-Watson analysis indicates no problematic autocorrelation within the residuals, supporting the reliability of the results. Additionally, the correlation appears to be slightly high, however the multicollinearity test verified that no multicollinearity between the variables is present (VIF values ranging between 1,660 and 2,513).

R-squared value of 0,325 suggest that approximately 32,5% of the variance in the customer perceived value can be explained by the personalization driver. R-squared value of 0,281 suggest that approximately 28,1% of the variance in the customer perceived value can be explained by the interactivity driver. R-squared value of 0,527 suggest that approximately 52,7% of the variance in the customer perceived value can be explained by the trust driver. R-squared value of 0,164 suggest that approximately 16,4% of the variance in the customer perceived value can be explained by the gamification driver. R-squared value of 0,521 suggest that approximately 52,1% of the variance in the customer perceived value can be explained by the service quality driver. R-squared value of 0,172 suggest that approximately 17,2% of the variance in the customer perceived value can be explained by the social interaction driver.

Table 7. *Pairwise relationship of customer perceived value with value drivers*

Perceived customer value				
Determinant	B	β	T	p
Personalization	0,529	0,570	10,404	<0,01
		$R^2 = 0,325$; F = 108,238; p <0,01		
Interactivity	0,688	0,530	9,377	<0,01
		$R^2 = 0,281$; F = 87,935; p <0,01		
Trust	0,805	0,726	16,820	<0,01
		$R^2 = 0,527$; F = 250,268 ; p <0,01		
Gamification	0,342	0,405	6,635	<0,01
		$R^2 = 0,164$; F = 44,029 ; p <0,01		
Service quality	0,89	0,722	15,645	<0,01
		$R^2 = 0,521$; F = 244,761 ; p <0,01		
Social interaction	0,528	0,415	6,836	<0,01
		$R^2 = 0,172$; F = 46,732 ; p <0,01		

Source: compiled by the author based on the results of the quantitative research

However, the concept that a single data-driven value driver determinant and customer perceived value have a totally independent relationship is not realistically correct. Therefore, after analyzing each factor's influence on customer perceived value independently, it was decided to examine and test the combined conceptual model variant. All six determinants have been put into a single regression equation (see table 8 and Annex 6).

Table 8. *Conceptual model of all value-drivers determinants relationship on perceived value*

	Perceived value			
Determinant	B	*β*	T	*p*
Constant	-0,194		-0,756	0,451
Personalization	0,091	0,099	1,838	0,67
Interactivity	0,060	0,047	0,838	0,403
Trust	0,392	0,354	5,787	<0,001
Gamification	0,069	0,082	1,799	0,073
Service quality	0,441	0,375	5,869	<0,001
Social interaction	0,003	0,002	0,043	0,965

Source: compiled by the author based on the results of the quantitative research

For a statistically correct analysis, some of the determinants were eliminated after being analyzed at a confidence level of 0,05 and final conceptual model created (Table 9). Values obtained during the regression analysis for the full model include: R^2 coefficient = 0,642, constant (C) = -0,194, and the Anova F test (F = 65,861, p<0,001), which confirmed the suitability of the data for the regression analysis. The Durbin-Watson test (1,898) indicates no significant autocorrelation in the residuals, further supporting the reliability of the regression results (see Annex 6). The multicollinearity test verified that there is non problematic multicollinearity between the variables, with VIF values raging from 1,270 to 2,513 (see Annex 6). To conclude, two out of the six initial determinants remained statistically significant: platform trust and service quality, both of which have a positive impact on customer perceived value. The R-squared value of 0,642 suggests that approximately 64,2% of the variance in the customer perceived value can be explained by the drivers within the model.

Table 9. *Conceptual model of statistically significant value drivers relationship on perceived customer value*

	Perceived value			
Determinant	B	*β*	T	*p*
Constant	0,032		0,050	0,960
Service quality	0,502	0,427	7,745	<0,001
Trust	0,487	0,439	7,7957	<0,001

Source: compiled by the author based on the results of the quantitative research

Hypothesis 1 (H1): personalization positively influences perceived customer value.

Based on the analyzed data the hypothesis (H1) stating that personalization on online sharing economy business platform positively influence the customer perceived value is **rejected**. In the simple regression model (see Table 7), personalization showed a statistically significant positive effect on perceived customer value (B = 0,529; β = 0,570; t = 10,404; p < 0,001; R^2 = 0,325). However, in the combined model (see Table 8), personalization lost its statistical significance (B = 0,091; β = 0,099; t = 1,838, p = 0,067). Results contradict earlier conclusion previously reached by other authors (Xu et al. 2011). In the current advanced and rapid-changing situation, personalized recommendations seem to have become a standard factor in the online ecosystem. The friction may be the data-processing paradox, customers like personalized experiences, however, they might be worried of how their data is collected.

Hypothesis 2 (H2): platform's trust positively influences perceived customer value.

Based on the analyzed data, the hypothesis (H2) stating that the greater customers' trust towards the platforms the more value they perceive from the usage of them is **accepted**. In the simple regression model (see Table 7), trust showed a statistically significant positive effect on perceived customer value (B = 0,805, β = 0,726, t = 16,820, p < 0,001; R^2 = 0,527). In the combined model (see Table 8), trust remained statistically significant (B = 0,392; β = 0,354; t = 5,787; p < 0,001), and in the final model (see Table 9) trust was confirmed as one of the two key drivers. The findings support the conclusions reached by earlier studies (Alshibly, H. H. 2015).

Hypothesis 3 (H3): service quality positively influences perceived customer value.

Based on the analyzed data, the hypothesis (H3) stating that the ease of use or quality of the platform positively influence the perceived customer value is **accepted**. In the simple regression model (see Table 7), service quality showed a strong statistical positive effect on perceived customer value (B = 0,890; β = 0,722; t = 15,645; p < 0,001; R^2 = 0,521). In the combined model (see Table 8), service quality remained statistically significant (B = 0,411; β = 0,375; t = 5,869; p < 0,001), and in the final model (see Table 9) it was confirmed as one of the two key drivers. Results are consistent with previous research findings (Kang, J. W., & Namkung, Y. 2024; Jiang, L., Jun, M., & Yang, Z. 2016).

Hypothesis 4 (H4): platform interactivity positively influences perceived customer value.

Based on the analyzed data, the hypothesis (H4) stating that the platform interactivity positively influences the value customer perceive of the platform is **rejected**. In the simple regression model (see Table 7), interactivity showed a statistically positive effect on perceived customer value (B = 0,688; β = 0,530; t = 9,377; p < 0,001; R^2 = 0,281). However, in the combined model (see Table 8), interactivity lost its statistical significance (B = 0,060; β = 0,047; t = 0,838; p < 0,403). The results reject previous conclusion reached by Roy, Singh, Sadeque, Harrigan and Coussement (2023). Excessive interactivity can be perceived as digital friction nowadays, especially in case the platform requires too many feedback or inputs from the customers' base.

Hypothesis 5 (H5): gamification positively influences perceived customer value.

Based on the analyzed data, the hypothesis (H5) stating that gamification features within the platform positively influence the perceived customer value is **rejected**. In the simple regression model (see Table 7), gamification showed a statistically positive effect on perceived customer value (B = 0,342; β = 0,405; t = 6,635; p < 0,001; R^2 = 0,164). However, in the combined model (see Table 8), gamification lost its statistical significance (B = 0,069; β = 0,082; t = 1,799; p < 0,073). The results are not consistent with previous research findings (Eisingerich et al. 2019; Jia, F., & Yu, J. 2025). Gamification was a major trend in previous years, however, the Italian market looks to value more different benefit which cannot be delivered by gamification features. Attractive costs, efficiency, may be valued more than a pleasant feeling of potentially earn discount or advantages while interact with a game.

Hypothesis 6 (H6): social interaction features positively influences perceived customer value.

Based on the analyzed data, the hypothesis (H6) stating that other customers' reviews or comments about products or services positively influence the perceived customer value is **rejected**. In the simple regression model (see Table 7), social interaction showed a statistically positive effect on perceived customer value (B = 0,528; β = 0,415; t = 6,836; p < 0,001; R^2 = 0,172). However, in the combined model (see Table 8), social interaction lost its significance (B = 0,003; β = 0,002; t = 0,043; p < 0,965). Results contradict the conclusions reached by earlier studies (Ngo, Nguyen, 2025). The global internet has been almost saturated by reviews, many of which are lately AI-generated and no longer spontaneously written by other human beings, which could lead to less reliability of customers to online reviews or comments. Social interaction may be actually seen as a baseline necessity for platforms to even exist.

2.6.4 User age as moderator analysis

Moderator regression analysis was used to examine whether the customers' age moderates the links between data-driven value drivers and customer perceived value. For the data analysis, 6 moderation equations were compiled based on the following logic: X (data-driven determinant) predicts Y (customer perceived value) under the influence of moderator M (customer age). Model 1 from SPSS's Hayes Process macro was used to run the moderator analysis. By integrating this model, it is possible to test interaction effects and determine whether the strength of the relationship changes at a different levels of moderator (Hair et al. 2021).

The moderator analysis indicates that all six interactions can be interpreted using the independent variable and the moderator as all R^2 coefficients are sufficient and statistically significant (p<0,001). However, when customer age was assessed as moderator, it was found out that customer age statistically moderates only one data-driven value driver (gamification) and the customer perceived value. Table 10 provides the interaction coefficients for the variables moderated by the customer age, and Annex 7 provides the moderator analysis matrix.

Table 10. *Customer age as moderator analysis results*

Independent variable (X)	Dependent variable (Y)	Moderator (W) and independent variable interaction			Moderator (W) influence		
		R^2	F	p	R^2 change	F	p

Personalization	Customer perceived value	0,331	36,717	<0,001	0,058	1,927	0,166
Interactivity	Customer perceived value	0,282	29,138	<0,001	0,001	0,170	0,896
Trust	Customer perceived value	0,533	84,985	<0,001	0,008	0,372	0,542
Gamification	Customer perceived value	0,179	16,197	<0,001	0,015	4,122	0,043
Service quality	Customer perceived value	0,529	83,398	<0,001	0,068	3,222	0,074
Social interaction	Customer perceived value	0,176	15,896	<0,001	0,010	0,282	0,596

Source: compiled by the author based on the results of the quantitative research

Hypothesis 7 (H7): customers age moderates the relationship between personalization and customer perceived value.

Values obtained from the analysis: R^2 change coefficient = 0,058, F = 1,927, p < 0,166. The moderator analysis shows that the relationship between personalization and customer perceived value is not empowered by the customer age (non-significant p-value). Based on these results, hypothesis (H7) stating that age moderates the relationship between personalization and customer perceived value is **rejected**.

Hypothesis 8 (H8): customer age moderates the relationship between platform trust and customer perceived value

Values obtained from the analysis: R^2 change coefficient = 0,008, F = 0,372, p < 0,542. The moderator analysis shows that the relationship between platform trust and customer perceived value is not empowered by customer age (non-significant p-value). Based on these results, hypothesis (H8) stating that age moderates the relationship between platform trust and customer perceived value is **rejected**.

Hypothesis 9 (H9): customer age moderates the relationship between service quality and perceived customer value.

Values obtained from the analysis: R^2 change coefficient = 0,068, F = 3,222, p < 0,074. The moderator analysis shows that the relationship between service quality and customer perceived value is not empowered by customer age (non-significant p-value). Based on these results, hypothesis (H9) stating that age moderates the relationship between gamification and customer perceived value is **rejected**.

Hypothesis 10 (H10): customer age moderates the relationship between interactivity and perceived customer value.

Values obtained from the analysis: R^2 change coefficient = 0,001, F = 0,170, p < 0,896. The moderator analysis shows that the relationship between interactivity and customer perceived value is not empowered by the customer age (non-significant p-value). Based on these results, hypothesis (H10) stating that age moderates the relationship between interactivity and customer perceived value is **rejected**.

Hypothesis 11 (H11): customer age moderates the relationship between gamification and customer perceived value.

Values obtained from the analysis: R^2 change coefficient = 0,015, F = 4,122, p < 0,043. The moderator analysis shows that the relationship between gamification and customer perceived value is empowered by customer age (significant p-value). Based on these results, hypothesis (H11) stating that age moderates the relationship between gamification and customer perceived value is **accepted**.

Hypothesis 12 (H12): customer age moderates the relationship between social interaction and customer perceived value.

Values obtained from the analysis: R^2 change coefficient = 0,010, F = 0,282, p < 0,596. The moderator analysis shows that the relationship between social interaction and customer perceived value is not empowered by customer age (non-significant p-value). Based on these results, hypothesis (H12) stating that age moderates the relationship between social interaction and customer perceived value is **rejected**.

The rejected hypothesis (H7, H8, H9, H10, H12) contradict the findings reported in previous studies (Molinillo, S. 2021; Fang et al. 2016), while (H11) is accepted, with gamification being more effective among older generations.

Finally, it is also relevant to note that hypotheses which have been rejected in this study, should be interpreted with methodological caution. Rejected hypotheses do not necessarily mean that there is absence of relationship between variables. Instead, it may reflect that the sample used in this research does not provide sufficient statistical evidence to confirm a significant relationship. Research conducted with different samples, larger populations, alternative platform categories, or different national contexts may lead to different results.

2.7 Conclusion of findings and recommendations

The complete investigation of the drivers influencing customer perceived value on sharing economy business platform involved the test of twelve hypothesis. Each of which attempted to find the relationship between different determinants and the customer perceived value. The finding revealed that three hypothesis were accepted, while nine rejected (see Table 11).

Table 11. *Hypothesis test results*

Hypothesis	Key statistics	Results
H1 - personalization positively influences perceived customer value	B = 0,529; β = 0,570; p<0,01 (model 1); p = 0,067 (model 2)	Rejected
H2 - platform's trust positively influences perceived customer value	B = 0,805; β = 0,726; p<0,001 (model 3)	Accepted
H3 - service quality positively influences perceived customer value	B = 0,890; β = 0,722; p<0,001 (model 3)	Accepted
H4 - platform interactivity positively influences perceived customer value	B = 0,688; β = 0,530; p<0,01 (model 1); p = 0,403 (model 2)	Rejected
H5 - gamification positively influences perceived customer value	B = 0,342; β = 0,405; p<0,01 (model 1); p = 0,073 (model 2)	Rejected
H6 - social interaction features positively	B = 0,528; β = 0,415; p<0,01 (model 1); p = 0,965 (model 2)	Rejected

influences perceived customer value		
H7 - customer age moderates the relationship between personalization and customer perceived value	R^2 change = 0,058; F = 1,927; p = 0,166	Rejected
H8 - customer age moderates the relationship between platform's trust and customer perceived value	R^2 change = 0,008; F = 0,372; p = 0,542	Rejected
H9 - customer age moderates the relationship between service quality and customer perceived value	R^2 change = 0,068; F = 3,222; p = 0,074	Rejected
H10 - customer age moderates the relationship between interactivity and customer perceived value	R^2 change = 0,001; F = 0,170; p = 0,896	Rejected
H11 - customer age moderates the relationship between gamification and customer perceived value	R^2 change = 0,015; F = 4,122; p = 0,043	Accepted
H12 - customer age moderates the relationship between social interaction and customer perceived value	R^2 change = 0,010; F = 0,282; p = 0,596	Rejected

Source: compiled by the author based on the results of the quantitative research.

Remark. Model 1: Pairwise regression; Model 2: Multiple regression; Model 3: Reduced multiple regression model

The empirical analysis of this research tested twelve hypotheses: six direct effect hypotheses (H1 – H6) examining how data-driven value drivers influence customer perceived value, and six moderation hypotheses (H7 – H12) trying to assess the role of customer age as moderator. The results showed that of the tested value drivers, platform trust and service quality emerged as significant predictors. Personalization, interactivity, gamification, and social interaction were statistically significant in simple pairwise regression, but once combined with the other drivers, they lost the significance. Based on this findings, some practical implications may be offered to sharing economy platform leaders operating or entering the Italian market.

Given trust emerged as the strongest predictor of the customer perceived value, platform managers should treat trust as their primary strategic priority while developing the defined platform. This means implementing transparent data privacy policies, ensuring consistent terms and conditions between platform's parties, and communicating security measures such as verified profiles, safe payment methods, and customer data protections. Trust, as also advised by the business expert interviewed while performing the pilot test for this study, is difficult to build but very easy to destroy. Therefore, proactive communication and action following any type of platform incident or data concern is essential.

Service quality was found as the second most significant driver, confirming that Italian customers' value perceptions are tied to operational reliability and ease of use. Platform managers, in this case, should invest in continuous improvement of information quality such as clear product description, search and navigation functionality with fast and intuitive item discovery, and rapid problem resolution processes. As seen in the pilot study, even minor friction points in the service experience can lead to significant customer drop-off. Additionally, service quality investigations or competitive comparison may be beneficial in order to keep the competitive advantage.

Although remaining value drivers were not significant in the overall model, it is important to emphasize that each of them play an important role when it comes to customer perceived value, as shown in the single regression tests.

Regarding the moderating role of customer age, only H11 was found statistically significant, which showed how age moderates the relationship between gamification and customer perceived value, being gamification more effective among older customers wihtin the Italian sharing economy platform ecosystem, with less impact toward the younger participants. In this instance, platforms with a substantial senior customer segment should consider age-targeted gamification strategies, such as loyalty reward programmes, milestone badges, and ad-hoc discounts, rather than applying gamification uniformly across all customer ages. For younger customers, resources and fundings previously allocated to gamification features may be invested and redirected toward trust enhancements or service quality improvements.

To conclude, even though the research did not find the demographic parameter, user age, as a strong moderator on the relationship between determinants and customer perceived value, platform leaders should continue to be aware of the various demands and requests of various customer age groups.

2.8 Scientific discussion

The results obtained in this study provide a useful insight into the relationship between the main data-driven customer value drivers and customer perceived value in the sharing economy online business platform context. Overall, the findings show that although all the chosen determinants were initially positively associated with customer perceived value, only platform’s trust and serviced quality remained statistically significant in the final multiple regression test. This suggests that in the specific context of this study, the effect of the other elements may be present at a general level, but not sufficiently strong to explain the perceived customer value independently once all the variables were considered together.

Results are partly consistent with the previous literature reviewed in the theoretical section. More precisely, the strong relevance of platform’s trust confirms the conclusions reached by (Alshibly H. H. 2015), who found emphasized that trust is a key factor influencing customer perceived value in the online environment. Similarly, the significance of service quality is in line with previous studies carried out by (Kang, J. W., & Namkung, Y. 2024 & Jiang, L., Jun, M., & Yang, Z. 2016) who highlighted the importance of the ease of use, information quality, and platform efficiency in shaping customer evaluations of business platforms. This research supports the idea that customers appear to attach greater value to platforms which are reliable and functional, especially when they are required to make purchases in the digital ecosystem.

Furthermore, the non-significance of personalization, interactivity, gamification, and social interaction contradict previous findings described by (Wu, G. 1999, March & Roy, S. K., Singh, G., Sadeque, S., Harrigan, P., & Coussement, K. 2023; Eisingerich, A. B., Marchand, A., Fritze, M. P., & Dong, L. 2019 & Jia, F., & Yu, J. 2025; Ngo, Nguyen, 2025), indicating that these factors may not act as independent value drivers in the same way as trust and service quality. There results differ from the initial expectations, where these variables were presented as positive contributors to perceived customer value. Potentially, these data-driven value drivers have become common in the online business environment and may consequently be perceived as standard requirements rather than distinctive factors. In addition, a possible interpretation is that their influence might be indirect, operating through service quality and trust instead of isolation or as separate determinants.

The moderator analysis also provides meaningful contribution to the research. The results indicate that customer age does not consistently moderate the relationship between all data-driven value drivers and customer perceived value, which means that the effect of these drivers is not equally different across age groups. This finding is only partially aligned with the existing literature, since (Santos, S. 2024 & Molinillo, S. 2021) showed in their studies how younger and older customers may value sharing economy business platforms features in different ways. However, in this thesis, age appears to play a limited role, which may indicate that platform evaluation is influenced by digital expectations than by generational differences alone. The presence of some age-related variation suggests that demographic characteristics should still be considered when analyzing customer value perception.

To sum up, the study confirms that customer perceived value in sharing economy business platforms is a multifaced concept, shaped by technological and behavioral elements. However, the results also show that not every data-driven value drivers have the same explanatory power, with service quality and trust being the most robust drivers. In practical terms, sharing economy business platforms leaders should not invest and focus only on attractive features, but should also ensure credibility, transparency, and efficient service delivery. From the theoretical perspective, this study contributes to the existing literature by showing that the influence of the chosen data-driven value drivers may depend on their combined effect, rather than in isolation.

2.9 Limitation of the study

The limitations of the study of the study are also important to be mentioned, and they should be taken into consideration when evaluating the results and modeling of the effect of customer data-driven value drivers and customer value creation on sharing economy business platform.

Firstly, while the research sample size of 227 valid respondents and the use of nonprobability convenience sampling approach are sufficient for statistical analysis, they do not ensure the findings of the research are representative outcomes, it would be recommended to employ a probabilistic sample technique, with consequent requirement of using a database for platform-specific users data.

Additionally, this research generalized sharing economy business platform, so it could be beneficial to explore the role of specific ones on the relative weight of each value driver. This study treated sharing economy platforms as homogeneous category, but the type of goods or service exchanged may be different and influence how customers are impacted by different drivers. Platform-specific studies could also lead to a more actionable insights for managers of individual platforms.

Moreover, the research was carried out interviewing only Italian customers, which may not be sufficient in order to have a holistic understanding whether the determinants studied are also relevant in the rest of the European market, even globally, or not. The dominance of trust and service quality in the Italian context could be a cultural trait, further investigation with northern or southern Europe could provide greater knowledge for business leaders.

Finally, this research focused on the examination of multiple data-driven value drivers. This approach limited the research depth, as only three statements were designed to each determinant in the questionnaire. For further research, it could be valuable to focus more on deeply understanding the complex components and structure of each of them by dedicating more constructs.

CONCLUSION

The literature review established a comprehensive conceptual framework by identifying six key data-driven customer value drivers in sharing economy business platforms: personalization, platform trust, service quality, interactivity, gamification, and finally social interaction. After consulting a wide range of academic sources across strategic management, digital platform theories, and customer behavior, it was demonstrated that customer value in online business platform contexts is no longer passively delivered by only one player, but actively co-created between both parties. The review revealed that while all six drivers have been discussed in prior studies as positive contributors to customer perceived value, was not tested in the Italian ecosystem. This gap justified the empirical investigation carried out in the second chapter. The conceptual scheme provided the theoretical foundation for hypothesis formulation and consequently the survey design. Additionally, the literature has also emphasized the evolving role of platform governance, the increasingly importance of network effects, and the value co-creation mechanisms, all of which presented the strategic significance of the six drivers chosen for empirical testing.

Furthermore, a quantitative research methodology was successfully designed and implemented to test the relationship between data-driven value drivers and perceived customer value in the Italian sharing economy platform environment. The research instrument used was a structured online questionnaire (Annex 1 and Annex 2) including 21 items measured on a 5-points Likert scale, adapted from validated constructs in the existing literature. Comprising also an initial control question, and demographic questions. The questionnaire led to a final sample of 227 eligible respondents who made at least one purchase on a sharing economy business platform in the three months preceding the survey. The data quality was confirmed through reliability analysis (with an overall Cronbach's alpha equal to 0,926, Table 3), normality test via Kolmogorov-Smirnov test (Table 4), and Spearman correlation analysis (Table 6). Pairwise simple linear regression analyses were performed for each driver independently (Table 7), followed by a combined regression model (Table 8), a reduced final model (Table 9), and moderation analyses for all six drivers with customer age as moderator (Table 10). This methodological approach enabled a robust and replicable empirical test of the conceptual model.

The empirical analysis identified platform trust and service quality the two most significant data-driven value drivers among Italian sharing economy platform customers. In the final regression model, trust and service quality explained roughly 59% of the variance in perceived customer value.

The other remaining four drivers, personalization, interactivity, gamification, and social interaction were statistically significant when analyzed singularly (Table 7), but lost their power in the combined model (Table 8), signaling that they operate mainly alongside platform trust and service quality rather than independently. This results suggest that Italian customers on sharing economy business platforms prioritize reliability, safety, and operational efficiency.

Regarding the moderating role of customer age, the moderation analysis demonstrated that age cannot be generalized as a moderator in this context. Out of the six moderation hypotheses tested, only H11 was accepted, stating that customer age statistically moderates the relationship between gamification and customer perceived value, with the effect of this driver being stronger among older respondents. This finding suggests that in the Italian ecosystem, age is not a dominant factor in shaping how different value drivers are perceived.

Finally, this research and the findings presented are scientifically and practically significant because of the holistic approach employed. Due to its scientific novelty and limited research in the field, this phenomena should be further explored in academic research, focusing on a more in-depth analysis of each determinant. To conclude, sharing economy business platform leaders should prioritize improvements of data-driven value drivers that have a strong positive impact on customer perceived value.

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SUMMARY

DATA-DRIVEN CUSTOMER VALUE DRIVERS: LEVERAGING SHARING ECONOMY BUSINESS PLATFORM CUSTOMERS DATA FOR ENHANCED VALUE CREATION

Francesco Fangarezzi

Master Thesis

Global business and Economic master programme

Faculty of Economics and Business Administration, Vilnius University

Supervisors Assoc. Prof. Dr. Aurelija Ulbinaitė, Vilnius 2026

71 pages, 11 tables, 5 figures, 63 references.

The main purpose of the master thesis is to identify determinants of data-driven customer value drivers on sharing economy business platforms that influences the most customer perceived value and examine the relationship between them.

The master thesis consists of three parts: the literature analysis, empirical research and its findings, conclusions and recommendations.

Literature analysis presents the online ecosystem and the sharing economy business platforms. Furthermore, it discusses different authors' perspective on data-driven determinants: personalization, interactivity, platform trust, gamification, service quality, social interaction, and introduces the concept of perceived customer value. The theoretical part is concluded with the connections between the described phenomena, the results of previous studies and the discussion of academics.

Following the literature analysis, empirical research was carried out to examine the relationship between data-driven customer value drivers and customer perceived value. In addition, moderator analysis of customer age was performed. A quantitative study was conducted, leading to 242 respondents completing the survey, with 227 eligible for further research. The results of the research were processed using SPSS software and Process macro by A. Hayes. Cronbach's Alpa coefficients were calculated to determine the alignment of the Likert scales of the construct. Spearman correlation was applied in order to establish a correlation between data-driven value drivers and customer perceived value. The study found that two out of six determinants positively affect customer perceived value: service quality and platform trust. Personalization, gamification, interactivity, and social interaction were found not to have statistical significance. Additionally, user age moderates the relationship between gamification and customer perceived value, mainly among older customers. Beside gamification, customer age did not influence any other relationship between described determinants and customer perceived value.

Given the scientific novelty and limited research on the topic, this phenomenon should be explored further. Sharing economy business platforms managers should prioritize and improve determinants that have positive impact on customer perceived value when operating in this specific field.

Keywords: business platform, sharing economy, customer perceived value, data-driven customer value drivers

SANTRAUKA

DUOMENIMIS GRĮSTI KLIENTŲ VERTĖS VEIKSNIAI: DALIJIMOSI EKONOMIKOS PLATFORMŲ KLIENTŲ DUOMENŲ PANAUDOJIMAS VERTĖS KŪRIMUI DIDINTI

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Darbą sudaro 71 puslapiai, 11 lentelių, 5 paveikslai, 63 nuorodos.

Pagrindinis šio darbo tikslas - nustatyti duomenimis pagrįstus klientų vertės veiksnius dalijantis ekonominėmis verslo platformomis, kurios daro įtaką labiausiai kliento suvokiamai vertei, ir išnagrinėti jų tarpusavio santykius.

Darbas sudarytas iš trijų dalių: literatūros analizė, empirinio tyrimo ir tyrimo rezultatų, išvadų ir rekomendacijų.

Literatūros analizė pristato internetinę ekosistemą ir dalijimosi ekonomikos verslo platformas. Be to, joje aptariama skirtinga autorių nuomonė apie duomenis lemiančius veiksnius: personalizavimą, interaktyvumą, platformos pasitikėjimą, žaidybinimą, paslaugų kokybę, socialinę sąveiką ir supažindinama su suvokiamos kliento vertės sąvoka. Teorinė dalis baigiama ryšiais tarp aprašytų reiškinių, ankstesnių tyrimų rezultatų ir akademikų diskusijų.

Remiantis literatūros analize buvo atliktas empirinis tyrimas, siekiant ištirti duomenimis pagrįstų klientų vertės veiksnių ir kliento suvokiamos vertės santykį. Be to, buvo atlikta moderatorinė klientų amžiaus analizė. Atliktas kiekybinis tyrimas, kuriame dalyvavo 242 respondentai, iš kurių 227 galėjo būti įtraukti į tolesni tyrimą. Tyrimo rezultatai apdoroti naudojant SPSS programinę įrangą ir A. Hayesas PROCESS makrokomandą. Konstrukcijos Likerto skalių išlygiavimui buvo naudojamas Cronbacho alfa koeficientas. Spearman koreliacija buvo taikyta siekiant nustatyti ryšį tarp duomenimis pagrįstų vertės veiksnių ir kliento suvokiamos vertės.

Tyrimas parodė, kad du iš šešių veiksnių teigiamai veikia kliento suvoktą vertę: paslaugų kokybę ir platformos pasitikėjimą. Nustatyta, kad personalizavimas, žaidybinimas, interaktyvumas ir socialinė sąveika neturi statistinės reikšmės. Taip pat, buvo nustatyta, kad vartotojų amžius modeliuoja ryšį tarp žaidybinimo ir kliento suvokiamos vertės, daugiausia tarp vyresnio amžiaus klientų. Be žaidybinimo, klientų amžius neturėjo įtakos jokiems kitiems santykiams tarp aprašytų lemiančių veiksnių ir kliento suvokiamos vertės.

Atsižvelgiant į mokslinę naujovę ir ribotus tyrimus šia tema, šis reiškinys turėtų būti toliau nagrinėjamas atliekant tolesnius akademinius tyrimus. Dalijimosi ekonomikos verslo platformų valdytojai, veikdami šioje konkrečioje srityje, turėtų teikti pirmenybę ir tobulinti veiksnius, darančius teigiamą poveikį kliento suvokiamai vertei.

Raktiniai žodžiai: verslo platforma, dalijimosi ekonomika, vartotojo suvokiama vertė, duomenimis grindžiami vertės kūrimo veiksniai

ANNEXES

Annex 1 *Customer value drivers and users' perceived value evaluation questionnaire*

Dear Respondent,

I am Francesco Fangarezzi, a master student at Vilnius University, currently attending Global Business and Economics program. I am carrying out a research for my master's thesis titled "Data-driven customer value drivers: leveraging business platform customers data for enhanced value creation". The purpose of this research is to determine how different features of online platforms such as personalization, trust, social interaction, service quality, gamification, and interactivity influence how much value consumers feel they receive from using them.

The survey is anonymous, and the data collected will be uniquely used for academic research purpose.

1. Have you purchased a product or service on a sharing economy online business platform (Amazon, AliExpress, Vinted, etc.) within the past three months?
    - Yes
    - No

Please answer the following questions based on your level of agreement to each statement from "strongly disagree" to "strongly agree".

2. Personalization

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I feel the personalized recommendations on the platform increases the value I get from the usage of it					
Personalized offers help me to find what I need in a more efficient way					
The platform's ability to adapt to my preferences makes it more valuable					

3. Interactivity

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree

The ability to give feedback or interact with the platform (through emails or feedback form) increases its value to me					
When the platform quickly responds to my input, I feel it adds value					
I find platforms more valuable when they allow me to shape my experience					

4. Gamification

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
The use of the gamification on business platforms improves the value I perceive of it					
Rewarding games or the possibility to receive discount or benefit, when present on business platform, makes me feel pleasant					
Playing games on online platforms allows me to obtain useful information for more cost-effective shopping, therefore higher perceived value					

5. Platform trust

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
The online platforms where I usually purchase products give the impression that they keep promises					
I believe online platforms tend to have my best interests in mind					
The online platforms are trustworthy					

6. Service quality

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree

The product information on the online platforms are usually easy to understand					
I can search for items that I need quickly on the online platforms I use					
The platforms solve the problems I encounter while purchasing a product quickly					

7. Social interaction

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Online customer reviews are a valuable tool for online purchasing					
Online customer comments regarding products or services provide helpful information					
The online customer reviews system contribute to increase the value I perceive of the platform					

8. Customer perceived value

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Compared to traditional businesses, sharing economy business platforms offer attractive product costs					
Compared to traditional businesses, sharing economy business platforms charge me fairly for similar products/services					
Compared to traditional businesses, sharing economy business platforms provide me more free services					

9. What is your current location?

- City

- Town
- Suburb
- Rural area

10. How old are you?

    Please type in your answer

11. What is your gender?
- Female
- Male
- Prefer not to say

12. What is the highest level of education you have completed?
- High school diploma
- Bachelor’s degree
- Master’s degree
- PhD

13. What is your current personal monthly income (after taxes)?
- Under 600 Eur
- From 601 to 1000 Eur
- From 1001 to 1500 Eur
- From 1501 to 2000 Eur
- Over 2000 Eur

Annex 2 *Customer value drivers and users' perceived value evaluation questionnaire in Italian*

Gentile Partecipante,

Mi chiamo Francesco Fangarezzi, studente magistrale presso la Vilnius University, attualmente iscritto al programma Global Business and Economics. Sto conducendo una ricerca per la mia tesi di laurea dal titolo "Data-driven customer value drivers: leveraging business platform customers data for enhanced value creation". Lo scopo di questa ricerca è determinare in che modo diverse caratteristiche delle piattaforme online, come personalizzazione, fiducia, interazione sociale, qualità del servizio, gamificazione e interattività, influenzino la quantità di valore che I consumatori percepisono nell'utilizzarle.

Il questionario è anonimo e I dati raccolti saranno utilizzati esculivamente per fini di ricerca accademica.

1. Hai comprato un prodotto o servizio su una piattaforma online della sharing economy (Amazon, Aliexpress, Ebay, Vinted, NordVPN, ecc.) nell'arco degli ultimi tre mesi?
    - Si
    - No

Si prega di rispondere alle seguenti domande indicando il proprio livello di accordo con ciascuna affermazione, da "decisamente in disaccorco" a "decisamente d'accordo".

2. Personalizzazione

	Decisamente in disaccordo	Disaccordo	Neutro	D'accordo	Decisamente d'accordo
Le raccomandazioni personalizzate che le piattaforme suggeriscono aumentano il valore che ottengo dall'utilizzo					
Le offerte personalizzate mi aiutano a trovare ciò di cui ho bisogno in modo più efficiente					
Le capacità della piattaforma di adattarsi alle mie preferenze la rende più utile					

3. Interazione

	Decisamente in disaccordo	Disaccordo	Neutro	D’accordo	Decisamente d’accordo
La possibilità di dare feedback o interagire con la piattaforma (tramite email o moduli di feedback) aumenta il valore che la piattaforma ha per me					
Quando la piattaforma risponde rapidamente alle mie richieste, questo aggiunge valore					
Trovo che le piattaforme siano migliori quando mi permettono di modellare la mia epserienza					

4. Gamificazione

	Decisamente in disaccordo	Disaccordo	Neutro	D’accordo	Decisamente d’accordo
La possibilità di giocare e ottenere sconti o premi sulla piattaforma aumenta il valore che percepisco di essa					
La presenza di giochi, quando presenti sulle piattaforme, mi fanno provare sensazioni positive					
Giocare all’interno delle piattaforme di negozi online mi permette di ottenere informazioni utilit per uno shopping più conveniente e, quindi, un maggiore valore percepito					

5. Fiducia

	Decisamente in disaccordo	Disaccordo	Neutro	D'accordo	Decisamente d'accordo
Le piattaforme online dove solitamente acquisto prodotti mi danno l'impressione di mantenere le promesse					
Credo che le piattaforme online tendano a tenere a mente I miei migliori interessi					
Le piattaforme online sono tendenzialmente affidabili					

6. Qualità del servizio

	Decisamente in disaccordo	Disaccordo	Neutro	D'accordo	Decisamente d'accordo
Le informazioni sui prodotti presenti sulle piattaforme online sono solitamente facili da comprendere					
Posso cercare rapidamente gli articoli di cui ho bisogno sulle piattaforme online che utilizzo					
Le piattaforme risolvono rapidamente I problemi che incontro durante l'acquisto di un prodotto					

7. Interazione sociali

	Decisamente in disaccorco	Disaccordo	Neutro	D'accordo	Decisamente d'accordo
Le recensioni dei clienti online sono uno strumento utile per gli acquisti online					

I commenti online dei clienti a riguardo di prodotti o servizi forniscono informazioni utili					
Il sistema di recensioni online contribuisce ad aumentare il valore che percepisco della piattaforma					

8. Valore percepito

	Decisamente in disaccordo	Disaccordo	Neutro	D'accordo	Decisamente d'accordo
Rispetto alle aziende tradizionali, le piattaforme di sharing economy offrono costi dei prodotti interessanti					
Rispetto alle aziende tradizionali, le piattaforme di sharing economy mi addebitano costi equi per prodotti/servizi simili					
Rispetto alle aziende tradizionali, le piattaforme di sharing economy mi offrono più servizi gratuiti					

9. Qual è la tua attuale area di residenza
    - Città
    - Paese / cittadina
    - Periferia
    - Area rurale
10. Qual è la tua fascia di età?

    Perfavore indica la tua età
11. Qual è il tuo genere?
    - Uomo
    - Donna

- Preferisco non rispondere

12. Qual è il più alto livello di istruzione che hai completato?
    - Diploma di scuola superiore
    - Laurea triennale
    - Laurea magistrale
    - Dottorato
13. Qual è il tuo reddito personale mensile attuale (al netto delle tasse)?
    - Meno di 600 eur
    - Da 601 a 1000 eur
    - Da 1001 a 1500 eur
    - Da 1501 a 2000 eur
    - Oltre I 2000 eur

Annex 3 *Demographic data of respondents in SPSS*

participant location

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	City	161	70.9	70.9	70.9
	Town	50	22.0	22.0	93.0
	Suburb	12	5.3	5.3	98.2
	Rural area	4	1.8	1.8	100.0
	Total	227	100.0	100.0	

participant gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Man	103	45.4	45.4	45.4
	Woman	123	54.2	54.2	99.6
	Prefer not to say	1	.4	.4	100.0
	Total	227	100.0	100.0	

participant education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Other	22	9.7	9.7	9.7
	high school	65	28.6	28.6	38.3
	bachelor degree	69	30.4	30.4	68.7
	master degree	59	26.0	26.0	94.7
	PhD	12	5.3	5.3	100.0
	Total	227	100.0	100.0	

participant income after taxes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	less than 600 eur	39	17.2	17.2	17.2
	between 601 and 1000	22	9.7	9.7	26.9
	between 1001 and 1500	50	22.0	22.0	48.9
	between 1501 and 2000	62	27.3	27.3	76.2
	over 2000 eur	54	23.8	23.8	100.0
	Total	227	100.0	100.0	

Annex 4 *Reliability and validity Analysis in SPSS*

Reliability Statistics - All

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.926	.928	21

Reliability Statistics - Personalization

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.872	.873	3

Reliability Statistics - Interactivity

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.699	.698	3

Reliability Statistics - Trust

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.796	.802	3

Reliability Statistics - Gamification

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.865	.865	3

Reliability Statistics - Service quality

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.807	.808	3

Reliability Statistics - Social interaction

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.796	.796	3

Reliability Statistics - Perceived value

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.868	.870	3

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Pers_0	.223	227	<.001	.840	227	<.001
Int_0	.195	227	<.001	.837	227	<.001
trust_0	.176	227	<.001	.892	227	<.001
gam_0	.097	227	<.001	.966	227	<.001
qual_0	.189	227	<.001	.843	227	<.001
socint_0	.229	227	<.001	.801	227	<.001
pv_0	.140	227	<.001	.902	227	<.001

a. Lilliefors Significance Correction

Annex 5 *Descriptive statistics of research data in SPSS*

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Pers_0	227	1	5	3.91	.987	.974
Int_0	227	1	5	4.15	.706	.499
trust_0	227	1	5	3.93	.826	.682
gam_0	227	1	5	2.92	1.082	1.171
qual_0	227	1	5	4.07	.779	.607
socint_0	227	1	5	4.17	.719	.518
pv_0	227	1	5	3.97	.916	.839
Valid N (listwise)	227					

Correlations

		Pers_0	Int_0	trust_0	gam_0	qual_0	socint_0	pv_0
Pers_0	Pearson Correlation	1	.484***	.601***	.396***	.541***	.308***	.570***
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001
	N	227	227	227	227	227	227	227
Int_0	Pearson Correlation	.484***	1	.534***	.253***	.599***	.549***	.530***
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001
	N	227	227	227	227	227	227	227
trust_0	Pearson Correlation	.601***	.534***	1	.425***	.672***	.369***	.726***
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001
	N	227	227	227	227	227	227	227
gam_0	Pearson Correlation	.396***	.253***	.425***	1	.323***	.161*	.405***
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	.015	<.001
	N	227	227	227	227	227	227	227
qual_0	Pearson Correlation	.541***	.599***	.672***	.323***	1	.567***	.722***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001
	N	227	227	227	227	227	227	227
socint_0	Pearson Correlation	.308***	.549***	.369***	.161*	.567***	1	.415***
	Sig. (2-tailed)	<.001	<.001	<.001	.015	<.001		<.001
	N	227	227	227	227	227	227	227
pv_0	Pearson Correlation	.570***	.530***	.726***	.405***	.722***	.415***	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	
	N	227	227	227	227	227	227	227

***. Correlation at 0.001(2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed).

Annex 6 *Impact of data-driven value drivers on customers perceived value in SPSS*

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.570[a]	.325	.322	.754	1.652

a. Predictors: (Constant), Pers_0
b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.593	1	61.593	108.238	<.001[b]
	Residual	128.037	225	.569		
	Total	189.630	226			

a. Dependent Variable: pv_0
b. Predictors: (Constant), Pers_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.897	.205		9.253	<.001
	Pers_0	.529	.051	.570	10.404	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.530[a]	.281	.278	.778	1.445

a. Predictors: (Constant), Int_0
b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	53.286	1	53.286	87.935	<.001[b]
	Residual	136.344	225	.606		
	Total	189.630	226			

a. Dependent Variable: pv_0
b. Predictors: (Constant), Int_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.112	.309		3.601	<.001
	Int_0	.688	.073	.530	9.377	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.726[a]	.527	.524	.632	1.927

a. Predictors: (Constant), trust_0

b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	99.856	1	99.856	250.268	<.001[b]
	Residual	89.774	225	.399		
	Total	189.630	226			

a. Dependent Variable: pv_0

b. Predictors: (Constant), trust_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.800	.204		3.915	<.001
	trust_0	.805	.051	.726	15.820	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.405[a]	.164	.160	.840	1.454

a. Predictors: (Constant), gam_0

b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.035	1	31.035	44.029	<.001[b]
	Residual	158.595	225	.705		
	Total	189.630	226			

a. Dependent Variable: pv_0

b. Predictors: (Constant), gam_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.966	.161		18.454	<.001
	gam_0	.342	.052	.405	6.635	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.722[a]	.521	.519	.635	1.686

a. Predictors: (Constant), qual_0
b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	98.803	1	98.803	244.761	<.001[b]
	Residual	90.827	225	.404		
	Total	189.630	226			

a. Dependent Variable: pv_0
b. Predictors: (Constant), qual_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.515	.225		2.291	.023
	qual_0	.849	.054	.722	15.645	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.415[a]	.172	.168	.835	1.271

a. Predictors: (Constant), socint_0
b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32.612	1	32.612	46.732	<.001[b]
	Residual	157.018	225	.698		
	Total	189.630	226			

a. Dependent Variable: pv_0
b. Predictors: (Constant), socint_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.763	.327		5.393	<.001
	socint_0	.528	.077	.415	6.836	<.001

a. Dependent Variable: pv_0

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.801[a]	.642	.633	.555	1.898

a. Predictors: (Constant), socint_0, gam_0, Pers_0, Int_0, trust_0, qual_0

b. Dependent Variable: pv_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	121.813	6	20.302	65.861	<.001[b]
	Residual	67.817	220	.308		
	Total	189.630	226			

a. Dependent Variable: pv_0

b. Predictors: (Constant), socint_0, gam_0, Pers_0, Int_0, trust_0, qual_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.194	.256		-.756	.451		
	Pers_0	.091	.050	.099	1.838	.067	.565	1.769
	Int_0	.060	.072	.047	.838	.403	.526	1.900
	trust_0	.392	.068	.354	5.787	<.001	.435	2.299
	gam_0	.069	.038	.082	1.799	.073	.788	1.270
	qual_0	.441	.075	.375	5.869	<.001	.398	2.513
	socint_0	.003	.066	.002	.043	.965	.603	1.660

a. Dependent Variable: pv_0

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.792[a]	.627	.623	1.687

a. Predictors: (Constant), trust_0, qual_0

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1069.351	2	534.675	187.924	<.001[b]
	Residual	637.319	224	2.845		
	Total	1706.670	226			

a. Dependent Variable: pv_0

b. Predictors: (Constant), trust_0, qual_0

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.032	.626		.050	.960
	qual_0	.502	.065	.427	7.745	<.001
	trust_0	.487	.061	.439	7.957	<.001

a. Dependent Variable: pv_0

Annex 7 *User age as moderator analysis in SPSS*

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

*******************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : pers_0
    W  : Age

Sample
Size:  227

*******************************************************************
*******
OUTCOME VARIABLE:
 pv_0

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .5750      .3306     5.1228    36.7175     3.0000   223.0000
.0000

Model
              coeff         se          t          p       LLCI
ULCI
constant    11.9113      .1505    79.1449      .0000    11.6147
12.2079
pers_0        .5465      .0525    10.4035      .0000      .4430
.6501
Age           .0060      .0144      .4173      .6769     -.0223
.0343
Int_1         .0068      .0049     1.3880      .1665     -.0029
.0165

Product terms key:
 Int_1    :        pers_0   x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
```

```
X*W      .0058     1.9266     1.0000   223.0000      .1665
----------
    Focal predict: pers_0   (X)
          Mod var: Age      (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.

DATA LIST FREE/
   pers_0     Age        pv_0       .
BEGIN DATA.
    -2.7313    -8.9692    10.5315
       .2687    -8.9692    11.9880
      2.2687    -8.9692    12.9590
    -2.7313    -2.9692    10.4560
       .2687    -2.9692    12.0350
      2.2687    -2.9692    13.0876
    -2.7313    11.5508    10.2732
       .2687    11.5508    12.1486
      2.2687    11.5508    13.3988
END DATA.
GRAPH/SCATTERPLOT=
 pers_0   WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----



Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

********************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : int_0
```

```
    W  : Age

Sample
Size:  227

**************************************************************************
OUTCOME VARIABLE:
 pv_0

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .5307      .2816     5.4980    29.1380     3.0000   223.0000
.0000

Model
              coeff         se          t          p       LLCI
ULCI
constant    11.8992      .1557    76.4336      .0000    11.5924
12.2060
int_0         .6883      .0745     9.2338      .0000      .5414
.8351
Age         -.0051      .0144     -.3530      .7245     -.0335
.0233
Int_1         .0008      .0058      .1306      .8962     -.0108
.0123

Product terms key:
 Int_1    :        int_0    x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0001      .0170     1.0000   223.0000      .8962
----------
    Focal predict: int_0    (X)
          Mod var: Age      (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.

DATA LIST FREE/
   int_0      Age        pv_0       .
BEGIN DATA.
    -1.4537    -8.9692    10.9542
      .5463    -8.9692    12.3171
     1.5463    -8.9692    12.9985
    -1.4537    -2.9692    10.9171
```

```
      .5463    -2.9692    12.2890
     1.5463    -2.9692    12.9750
    -1.4537    11.5508    10.8271
      .5463    11.5508    12.2212
     1.5463    11.5508    12.9183
END DATA.
GRAPH/SCATTERPLOT=
 int_0    WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----



Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : trust_0
    W  : Age

Sample
Size:  227

**************************************************************************
*******
OUTCOME VARIABLE:
 pv_0

Model Summary
         R       R-sq        MSE          F        df1        df2
p
      .7304      .5334     3.5708    84.9854     3.0000   223.0000
.0000
```

```
Model
              coeff         se          t          p       LLCI
ULCI
constant    11.9028      .1256    94.7687      .0000    11.6552
12.1503
trust_0       .8063      .0511    15.7667      .0000      .7055
.9070
Age          -.0213      .0118    -1.8089      .0718     -.0446
.0019
Int_1        -.0027      .0044     -.6101      .5424     -.0114
.0060

Product terms key:
 Int_1    :        trust_0  x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0008      .3723     1.0000   223.0000      .5424
----------
    Focal predict: trust_0  (X)
          Mod var: Age      (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.

DATA LIST FREE/
   trust_0    Age        pv_0       .
BEGIN DATA.
    -2.7974    -8.9692     9.7714
      .2026    -8.9692    12.2624
     2.2026    -8.9692    13.9231
    -2.7974    -2.9692     9.6884
      .2026    -2.9692    12.1311
     2.2026    -2.9692    13.7596
    -2.7974    11.5508     9.4876
      .2026    11.5508    11.8134
     2.2026    11.5508    13.3639
END DATA.
GRAPH/SCATTERPLOT=
 trust_0  WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : gam_0
    W  : Age

Sample
Size:  227

**************************************************************************
*******
OUTCOME VARIABLE:
 pv_0

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .4230      .1789     6.2840    16.1971     3.0000   223.0000
.0000

Model
              coeff         se          t          p       LLCI
ULCI
constant    11.9371      .1675    71.2866      .0000    11.6071
12.2671
gam_0         .3383      .0518     6.5317      .0000      .2362
.4403
Age           .0142      .0159      .8928      .3729     -.0172
.0456
Int_1         .0089      .0044     2.0302      .0435      .0003
.0176

Product terms key:
 Int_1    :        gam_0    x        Age

Test(s) of highest order unconditional interaction(s):
```

```
       R2-chng           F        df1        df2          p
X*W      .0152     4.1217     1.0000   223.0000      .0435
----------
    Focal predict: gam_0    (X)
          Mod var: Age      (W)

Conditional effects of the focal predictor at values of the
moderator(s):

        Age     Effect         se          t          p       LLCI
ULCI
    -8.9692      .2580      .0667     3.8700      .0001      .1266
.3894
    -2.9692      .3117      .0540     5.7688      .0000      .2052
.4182
    11.5508      .4416      .0708     6.2345      .0000      .3020
.5812

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.

DATA LIST FREE/
   gam_0      Age        pv_0       .
BEGIN DATA.
    -3.7621    -8.9692    10.8390
      .2379    -8.9692    11.8709
     3.2379    -8.9692    12.6449
    -3.7621    -2.9692    10.7223
      .2379    -2.9692    11.9690
     3.2379    -2.9692    12.9041
    -3.7621    11.5508    10.4398
      .2379    11.5508    12.2063
     3.2379    11.5508    13.5312
END DATA.
GRAPH/SCATTERPLOT=
 gam_0    WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----



Run MATRIX procedure:
```

```
***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : qual_0
    W  : Age

Sample
Size:  227

**************************************************************************
*******
OUTCOME VARIABLE:
 pv_0

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .7271      .5287     3.6067    83.3978     3.0000   223.0000
.0000

Model
              coeff         se          t          p       LLCI
ULCI
constant    11.9012      .1261    94.4108      .0000    11.6528
12.1496
qual_0        .8585      .0544    15.7944      .0000      .7513
.9656
Age           .0011      .0120      .0918      .9269     -.0226
.0248
Int_1         .0081      .0045     1.7949      .0740     -.0008
.0169

Product terms key:
 Int_1    :        qual_0   x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0068     3.2218     1.0000   223.0000      .0740
----------
    Focal predict: qual_0   (X)
```

```
          Mod var: Age      (W)

Conditional effects of the focal predictor at values of the
moderator(s):

        Age     Effect         se          t          p       LLCI
ULCI
    -8.9692      .7862      .0642    12.2429      .0000      .6597
.9128
    -2.9692      .8345      .0546    15.2801      .0000      .7269
.9422
    11.5508      .9515      .0788    12.0670      .0000      .7961
1.1068

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.

DATA LIST FREE/
   qual_0     Age        pv_0       .
BEGIN DATA.
    -2.1982    -8.9692    10.1630
      .8018    -8.9692    12.5217
     1.8018    -8.9692    13.3079
    -2.1982    -2.9692    10.0634
      .8018    -2.9692    12.5670
     1.8018    -2.9692    13.4016
    -2.1982    11.5508     9.8225
      .8018    11.5508    12.6768
     1.8018    11.5508    13.6283
END DATA.
GRAPH/SCATTERPLOT=
 qual_0   WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----


Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
```

```
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

******************************************************************
*******
Model  : 1
    Y  : pv_0
    X  : socint_0
    W  : Age

Sample
Size:  227

******************************************************************
*******
OUTCOME VARIABLE:
 pv_0

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .4197      .1762     6.3050    15.8957     3.0000   223.0000
.0000

Model
              coeff         se          t          p       LLCI
ULCI
constant    11.9020      .1668    71.3657      .0000    11.5733
12.2306
socint_0      .5227      .0791     6.6115      .0000      .3669
.6785
Age          -.0149      .0149     -.9972      .3198     -.0442
.0145
Int_1        -.0032      .0060     -.5306      .5962     -.0150
.0086

Product terms key:
 Int_1    :        socint_0 x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0010      .2816     1.0000   223.0000      .5962
----------
    Focal predict: socint_0 (X)
          Mod var: Age      (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce
plot.
```

```
DATA LIST FREE/
   socint_0   Age        pv_0       .
BEGIN DATA.
    -1.5154    -8.9692    11.2000
      .4846    -8.9692    12.3023
     2.4846    -8.9692    13.4047
    -1.5154    -2.9692    11.1397
      .4846    -2.9692    12.2039
     2.4846    -2.9692    13.2682
    -1.5154    11.5508    10.9939
      .4846    11.5508    11.9659
     2.4846    11.5508    12.9378
END DATA.
GRAPH/SCATTERPLOT=
 socint_0 WITH     pv_0     BY       Age      .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```