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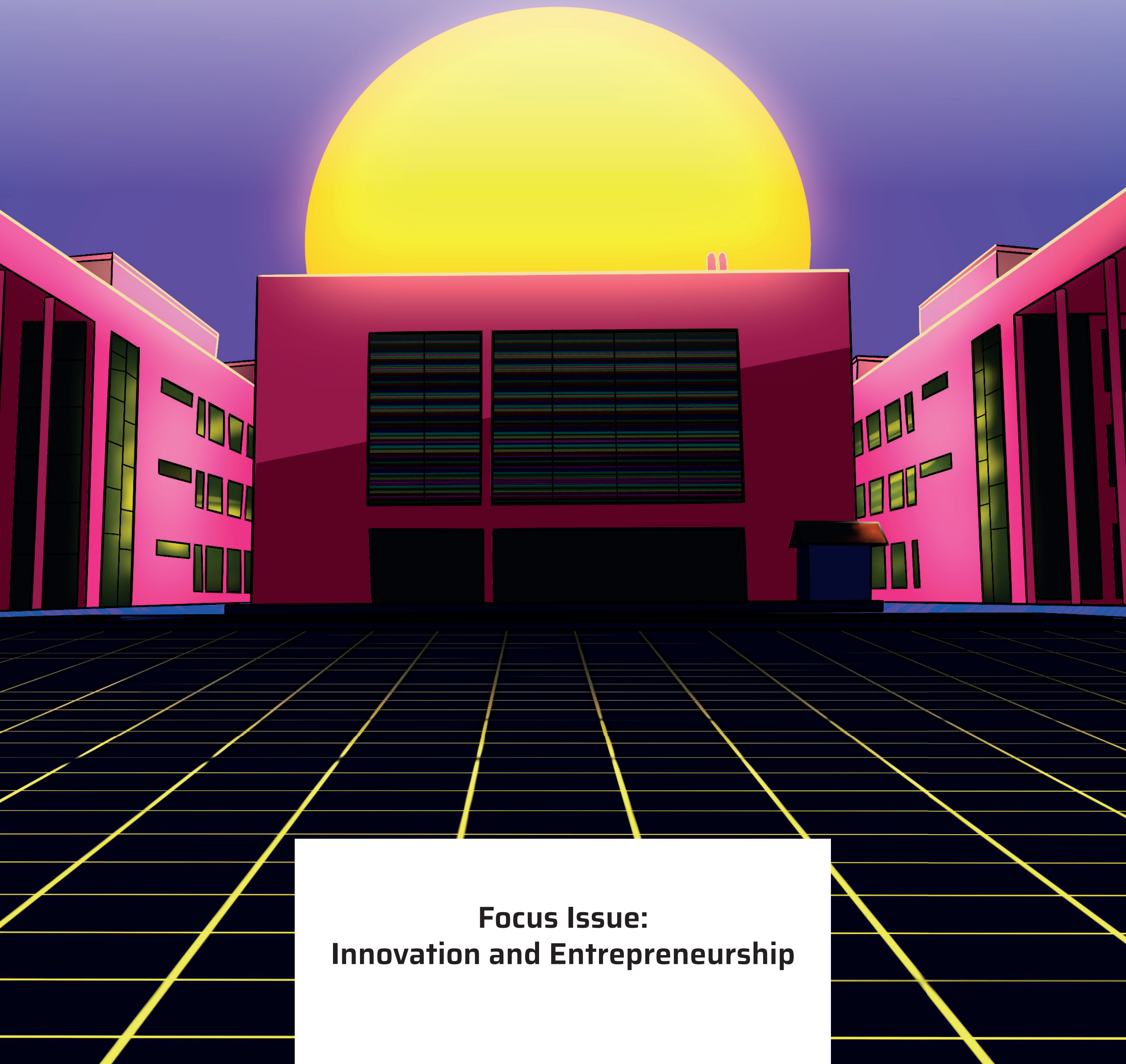

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CONTENT

Editors' Preamble

It is with great pleasure that we present the second official edition of the *Journal of Applied Interdisciplinary Research (JAIR)*. Building on the momentum of our inaugural volume, we are delighted to announce that, beginning this year, JAIR will publish at least two volumes annually: one in the middle of the year and one at year's end. This new approach is aimed at ensuring faster, more efficient publication of innovative research from our community.

From the outset, JAIR, like the *Bavarian Journal of Applied Sciences*, also published by the Deggendorf Institute of Technology, has been committed to rigorous peer review and to diamond open-access publishing, with absolutely no cost to authors. We firmly believe that this approach allows research to be shared internationally, across platforms and regions, enabling a fairer and more inclusive approach to publishing. We remain dedicated to this mission and are excited to expand our efforts by collaborating with other journals and encouraging open science in every aspect of our work.

The focus of this volume is on new ideas and innovation. We thank the authors for their insightful contributions, which highlight the creative and forward-thinking research happening within the applied sciences:

Pia Drechsel, Stephanie Jordan, Tatjana Seidel, Amelie Velten, Daniel Kusterer, Angela Hatzenbühler, Alexander H. Kracklauer: From Necessity to Pleasure: The Impact of Hedonic Motivation and Performance Expectancy on Acceptance of Online Grocery Shopping Apps in Germany

Kerstin Haeckel, Stephan Husung, Christine Wünsche: Digitization Technologies to Ensure Production Conformity

Maike Netscher, Stephanie Jordan, Anna Mast, Sebastian Kundrath, Hannes Lutz, Lukas Mader, Alexander H. Kracklauer: Improving Customer Experience Using Smart Technologies in Smart Stores

At its core, JAIR exists to champion interdisciplinary approaches. We firmly believe that true innovation emerges when research transcends traditional boundaries and engages with perspectives from multiple disciplines. By fostering a space for such collaboration, we strive to advance applied research that is both relevant and transformative. We would also like to extend our deepest thanks to our reviewers, whose expertise and dedication ensure the quality and integrity of each article we publish. We warmly welcome reviewers from all fields and invite you to join us in building JAIR into a vibrant, open-access platform; one that encourages dialogue and partnership across disciplines and borders. With each issue, we grow our foundation of accessible, impactful research, furthering our commitment to the international applied sciences community.

Thank you for your continued support and for being part of our journey.

Michelle J. Cummings-Koether & Kristin Seffer
Editors, *Journal of Applied Interdisciplinary Research (JAIR)*

From Necessity to Pleasure: The Impact of Hedonic Motivation and Performance Expectancy on Acceptance of Online Grocery Shopping Apps in Germany

Pia Drechsel*, Stephanie Jordan*, Tatjana Seidel*, Amelie Velten*, Daniel Kusterer*, Angela Hatzenbühler*, Alexander H. Kracklauer*

ABSTRACT

This study investigates key factors influencing German consumers' acceptance of online grocery shopping (OGS) apps. Despite the growing popularity of e-commerce, research on OGS app adoption in Germany remains limited. We applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to examine factors affecting acceptance and behavioral intention to use OGS apps. A quantitative approach with a convenience sample was employed in Germany. Data analysis involved principal component analysis followed by multiple linear regression analyses using IBM SPSS 28. Results showed that performance expectancy, hedonic motivation, and previous use of OGS apps significantly influenced behavioral intention. The UTAUT2 model's predictive probability was highest when considering control variables such as gender, age, and previous app use. Our findings contribute to understanding OGS app adoption in Germany and suggest practical implications, including expanding delivery zones to rural areas. This research addresses the knowledge gap in OGS app acceptance in Germany and provides insights for researchers and practitioners in the food retail sector.

KEYWORDS

Online grocery shopping apps, German retail, UTAUT2 model, behavioral intention

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1. Introduction

The advent of online grocery shopping (OGS) apps has revolutionized the way consumers purchase their daily necessities, offering unprecedented convenience and accessibility (Shroff et al., 2024). In recent years, OGS has experienced significant growth worldwide (Dillahunt et al., 2019). It allows users to order groceries conveniently on the internet and have them delivered to their desired location by the provider (Al-nawayseh et al., 2013; Musikavanhu & Musakuro, 2023). In 2022, the internet sales of food, including beverages and tobacco, accounted for 2.4 % of retail sales in Germany. This share has been steadily increasing since 2014 (Handelsverband Deutschland (HDE) e.V., 2024). Additionally, online grocery sales increased significantly in Germany from 2014 to 2022. By 2023, around EUR 11.3 billion had already been generated from groceries purchased online (Bundesverband E-Commerce und Versandhandel Deutschland (BEVH) e.V., 2024). Due to the rising demand for OGS apps, more and more providers—for example, Flink and Gorillas—have entered the German market. Users can choose the app that best suits their needs (Handelsverband Deutschland (HDE) e.V., 2024). Yet many customers have not yet adopted OGS apps despite their increasing popularity (Brüggemann et al., 2024).

The shift in consumer behavior toward online shopping requires traditional brick-and-mortar stores to adapt by enhancing their online presence and integrating digital solutions into their business strategies (Shroff et al., 2024). Retailers might need to invest in new technologies and logistics to support online orders and deliveries, including efficient supply chain management systems, warehouse automation, and last-mile delivery solutions (Frank & Peschel, 2020).

Although extensive research has been conducted on the factors affecting acceptance of OGS apps during and after the COVID-19 pandemic (Asgari et al., 2023; Gruntkowski & Martinez, 2022; Shen et al., 2022; Younes et al., 2022), as well as their adoption in various countries, including South Africa (Musikavanhu & Musakuro, 2023), India (Gupta & Kumar, 2023), the Netherlands (Verhoef & Langerak, 2001), the United States (Gillespie et al., 2022) and Thailand (Driediger & Bhatiasevi, 2019), there is a need to better understand consumers' usage intentions relative to these apps in Germany. Studies in the German context have focused predominantly on the pandemic period, examining the perspectives of retailers or elderly consumers (Braun & Osman, 2024; Hansson et al., 2022; Kvalsvik, 2022). However, the primary users of OGS apps are typically younger individuals between 20 and 29 years old residing in urban areas (Handelsverband Deutschland (HDE) e.V, 2024).

The purpose of this research was to fill a research gap identified by Monoarfa et al. (2024) and Klepek and Bauerová (2020) by investigating the factors that influence consumers' acceptance of OGS apps and their hesitancy about continuing to use them. The study aimed to explore the implications of broadly implementing OGS apps and provide insights to app developers and retailers who want to implement them. Therefore, seven hypotheses were tested based on an extension of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The UTAUT2 model is an extended version of the original UTAUT model that was developed to better explain technology acceptance, particularly in consumer contexts (Venkatesh et al., 2012). It extends the original framework by incorporating additional factors such as hedonic motivation, such as the pursuit of pleasure and enjoyment, price value, and habits, which significantly influence consumer acceptance and use of new technologies (Indrawati et al., 2022). Hedonic motivations can lead to increased consumer impulsiveness and more extended engagement with shopping platforms, thereby enhancing the overall shopping experience (Yim et al., 2014). This study examined the role of hedonic motivations in the context of OGS apps to understand how pleasure-driven factors impact user intentions. The primary objectives of this research were to

- apply technology adoption theories to understand the acceptance and usage patterns of OGS apps.
- identify the key factors influencing the intention to use OGS apps in Germany.

In addition, the model considered control variables such as age, gender, and previous use (Singh & Söderlund, 2020) to ensure a comprehensive analysis. Although this study employed a convenience sample, unlike previous studies, a video based on a market analysis that explains all essential functionalities of OGS apps, such as automatic location detection and digital shopping lists, was produced. This ensured that the questionnaire could be answered effectively by both users and non-users. Furthermore, this study examined not only internationally known apps such as Flink and Gorillas but also apps unique to Germany, including Flaschenpost and the REWE delivery service app.

By addressing this under-researched area, we aimed to provide a comprehensive understanding of the motivations and barriers associated with OGS app usage, thereby contributing valuable insights into consumer behavior and retailing. The structure of this paper is as follows: The following section presents the theoretical background, including the UTAUT2 model. Subsequently, we detail the methodology and data collection process and discuss the survey participants' demographics. Then, we examine the statistical analysis and present the results. Finally, the managerial implications of the findings are discussed, providing insights for practitioners on how to enhance the adoption and usage of OGS apps.

2. Theoretical Background

This study applied the UTAUT2 model by Venkatesh et al. (2012) to examine consumer behavior relative to the acceptance of OGS apps. The application of the UTAUT2 model was based on questions about several factors that were progressively asked of the technology user. These factors included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention (Venkatesh et al., 2012). Well-founded predictions could be made about whether OGS apps would be accepted with the information generated from these factors. The following segments describe how the factors were applied in the UTAUT2 model.

Performance Expectancy

When technology is used to complete a task or achieve a goal, performance expectancy (PE) describes the degree to which a person believes the outcome will be achieved (Park et al., 2007; Venkatesh et al., 2003). The PE construct is considered the strongest and most significant predictor of intention (Alalwan et al., 2017; Hassan et al., 2015; Musakwa & Petersen, 2023; Venkatesh et al., 2003). In this study, PE reflected the app user's expectation of an online grocery shopping experience. Factors that lead to an improved overall experience when using an app include, for example, an easy ordering process, an extensive product selection, and the timely and reliable delivery of groceries (Venkatesh, 2006). Accordingly, we hypothesized that having an ordering process that meets high-performance expectations could influence the acceptance of OGS apps.

H01 *Expected performance positively influences the behavioral intention to use OGS apps.*

Effort Expectancy

Whether the use of the technology is perceived as easy is reflected in effort expectancy (EE) (Venkatesh, 2006). OGS apps are evaluated for user-friendliness by the consumer, whose perception of ease of use plays an important role (Park et al., 2007). The usability of grocery shopping apps is characterized by factors that meet a reasonable expectation of effort, such as user-friendly interfaces, self-explanatory ordering processes, search functions, and different payment options. Therefore, we formulated the following hypothesis for this component:

H02 *EE positively influences the behavioral intention to use OGS apps.*

Social Influence

The extent to which factors such as social media, social norms, or product recommendations from friends and family influence the use of OGS apps was examined in this study through the consideration of social influence (SI). The SI of a particular technology defines individuals' perception of the importance that others place on its use (Venkatesh et al., 2003; Zolfaghari et al., 2022). The UTAUT2 model was used to examine whether and to what extent social factors influence the user's decision to order food through the app. For instance, personal recommendations may influence a decision whether to use an OGS app or shop at a regular supermarket.

H03 *SI positively affects the behavioral intention to accept OGS apps.*

Facilitating Conditions

Another component of the UTAUT2 model is facilitating conditions (FC) (Venkatesh, 2006). The FC are primarily intended to catch and support users who are uncertain about using the apps as that uncertainty may cause them to discontinue their use (Morris et al., 2005). To make OGS apps accessible and understandable to all age groups, support systems such as customer support and training on how to use the apps are essential.

H04 *FC positively influences the behavioral intention to accept OGS apps.*

Hedonic Motivation

The satisfaction and enjoyment derived from using OGS applications can serve as a source of hedonic motivation (HM) for continued usage (Brown & Venkatesh, 2005). Emotional factors are deemed significant in the development of OGS applications (Thong et al., 2006). Attributes such as age, origin, and gender influence hedonic motivation, as individuals find different aspects pleasurable based on their circumstances (Yim et al., 2014). Experiences such as discovering new products, enjoying a streamlined shopping process, or receiving personalized recommendations can contribute to the desired satisfaction from the application (Taglinger et al., 2023).

H05 *HM positively influences the behavioral intention to accept OGS apps.*

Price Value

Price value (PV) is the customer's perception of the value received in exchange for money (Brown & Venkatesh, 2005). This prompts consideration of the extent to which the benefits of an OGS app outweigh its cost. For a technology to be successful in the long run, its benefits must be superior to the financial costs (Zeithaml, 1988). For instance, high delivery costs may discourage a user from utilizing OGS apps. Additionally, age and gender play a role in people's attitudes toward value for money (Deaux & Lewis, 1984).

H06 *The expected PV positively influences the behavioral intention to accept OGS apps.*

Habit

The process by which behavior becomes automated, transitioning from the initial stages of learning to frequent utilization of technology, is defined as habit (HA) (Limayem et al., 2007; Venkatesh et al., 2012). OGS apps should be adopted more frequently due to their substantial benefits, including time efficiency and convenience for customers, according to Verhoef and Langerak (2001). Additionally, the habitual use of these apps can enhance the intention to use them, as it facilitates the acceptance and integration of this innovative service into consumers' everyday routines. This study investigated the habitual use of Online Grocery Shopping (OGS) applications to ascertain the frequency and regularity with which groceries were ordered through these platforms. The development of habitual use of OGS applications was examined under the following hypothesis.

H07 *HA positively influences the behavioral intention to accept OGS apps.*

Behavioral Intention

Behavioral intention (BI) is a person's intention to do something—in this case, to use an OGS app. Factors that influence BI include how skillfully a customer uses the app, whether the benefits of the app are perceived as such, and whether the app has satisfied users in the social environment (Liu et al., 2019). The usage behavior of OGS app consumers is influenced by their expectations of performance and effort, the social environment, facilitating technological circumstances, hedonic motivation, the perceived price-performance ratio, and the habit of purchasing groceries via an app. This section of the UTAUT2 encompasses the factors previously discussed, making BI a dependent variable and the principal component of this analysis (Musikavanhu & Musakuro, 2023), as seen in Figure 1.

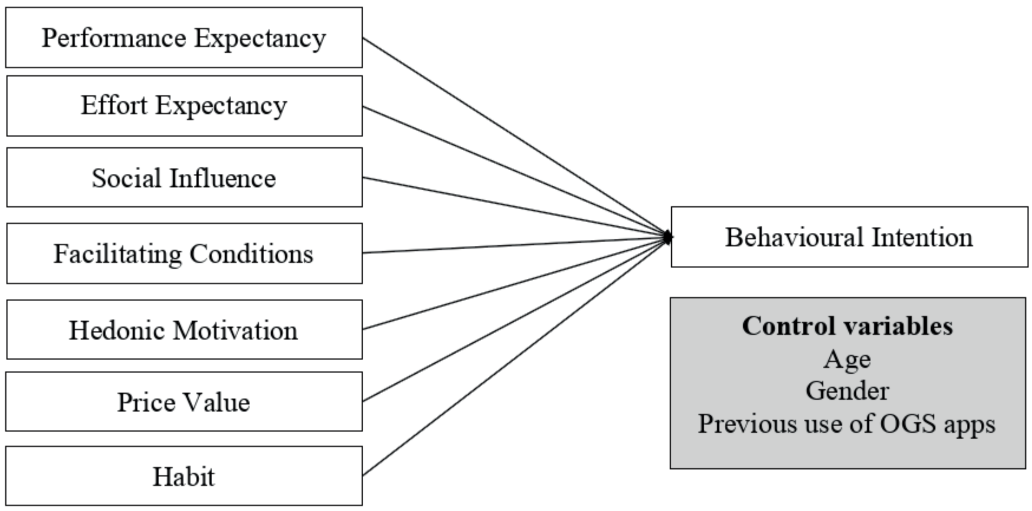

Figure 1: UTAUT2 Model and Control Variables.
Source: Venkatesh et al. (2012)

This study considered several control variables to ensure a robust analysis of the factors influencing the intention to use OGS apps. These control variables included age, gender, and previous use of OGS apps (Frank & Peschel, 2020). Age is critical as it can influence technology adoption, with younger individuals often being more open to new technologies (Braun & Osman, 2024). Gender was also considered, as research has shown that men and women may have different attitudes toward technology use and other related behaviors (Qazi et al., 2022). Previous use of OGS apps was included to account for familiarity and experience with the technology, which can significantly impact the intention to continue using the technology. We incorporated these control variables to provide a nuanced understanding of the determinants of OGS app usage intentions.

3. Methodology

Our study was conducted across Germany using an online questionnaire. For the analysis, we collected postal codes (*Postleitzahlen, PLZ*) and additional information on the population size of the participants' residential areas. This allowed us to categorize the regions as either rural or urban, providing a nuanced understanding of the data.

As we distributed the survey via the Internet, German citizens from various regions could participate, ensuring an accurate representation of current attitudes toward OGS apps in Germany. Additionally, no personally identifiable information was gathered that could influence the outcomes. The target audience consisted of German residents, regardless of their familiarity with OGS. The entire methodology and approach are illustrated in the flowchart in Figure 2.

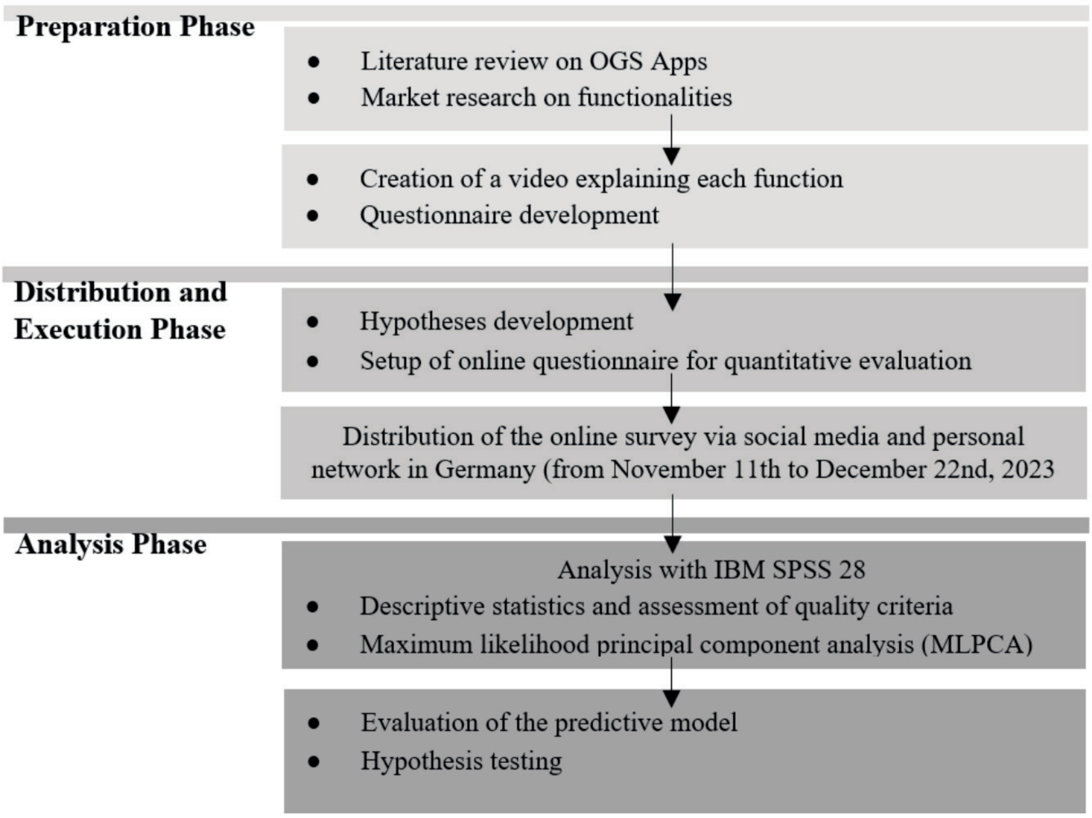

Figure 2: Flow Chart of Methodology.
Source: Created by the authors.

The survey structure was inspired by work from Netscher et al. (2024) with an explanatory video created by the research team, which introduced the OGS apps to the participants (cf. Appendix). This video illustrated the entire customer journey, starting with registration and address entry, followed by the grocery shopping experience, and concluding with the processing and payment of the order. Each action was depicted with in-app scenes, accompanied by subtitles written by the researchers and audio dubbing to describe the processes shown. The essential functions of OGS apps were demonstrated using anonymized brands to maintain neutrality.

Following the introduction, participants were asked general questions about their experience with OGS apps and their preferred functionalities for optimal usage. The main section of the survey measured the UTAUT2 constructs, with each item evaluated using a 7-point Likert scale ranging from 1 *(strongly disagree)* to 7 *(strongly agree)* (cf. Table 1). As the survey was conducted in Germany, the statements were translated into German, starting from the UTAUT2 model validated questions published by Harborth and Pape (2018) and refined based on the recommendations of a native speaker, following the approach of Taglinger et al. (2023). The survey was pretested for comprehensibility with members of the target audience.

In the final part of the questionnaire, information on the control variables was collected, including the respondents' demographic details (e.g., gender, age, educational status, and income level) and whether they had used OGS apps previously.

Model Constructs	*Items*
PE (Performance Expectancy)	PE1: I find food delivery apps useful in my daily life. PE2: Using such an app increases my chances of achieving things that are important to me. PE3: Using such apps helps me complete my shopping faster. PE4: Using food delivery apps increases my productivity.
EE (Effort Expectancy)	EE1: It is easy for me to handle these apps. EE2: My use of the apps is clear and understandable. EE3: I find using food delivery apps easy. EE4: It is easy for me to become skilled at using the apps.
SI (Social Influence)	SI1: People who are important to me think that I should use such apps. SI2: People who influence my behavior think that I should use such apps. SI3: People whose opinions I value prefer that I use food delivery apps.
FC (Facilitating Conditions)	FC1: I have the necessary resources to use such apps. FC2: I have the necessary knowledge to use these apps. FC3: These apps are compatible with other technologies and applications I use. FC4: I can get help from others when I have difficulties using these apps.
HM (Hedonic Motivation)	HM1: Using food delivery apps is fun. HM2: Using food delivery apps is enjoyable. HM3: Using the apps is very entertaining.
HA (Habit)	HA1: Using such apps has become a habit for me. HA2: I am addicted to using food delivery apps. HA3: I must use food delivery apps. HA4: Using these apps has become something natural for me.
PV (Price Value)	PV1: Food delivery apps are reasonably priced. PV2: The apps offer good value for the money. PV3: At the current price, these apps offer good value.
BI (Behavioral Intention)	BI1: I intend to use food delivery apps in the future. BI2: I will try to use food delivery apps in my daily life. BI3: I plan to continue using such apps regularly.

Table 1: Constructs with Scale Items and Sources.
Source: Harborth and Pape (2018)

The survey was distributed through various social media platforms like Facebook, Instagram, WhatsApp, and LinkedIn. The data collection took place from November 11th to December 22nd, 2023. After excluding respondents under 18, incomplete questionnaires, and those with repeated responses without variance, the final convenience sample consisted of 181 participants. Of these, 58.9 % were female and 41.1 % male, with a mean age of 33.66 years (SD = 11.44; range = 19–67 years) and an average net household income of around €3,000 per month. The gender distribution of the OGS app users was balanced, with 47.9 % being male and 52.1 % female. Additionally, 62.8 % of users were under age 35, indicating a correlation between age and the use of OGS apps (Rakhman et al., 2021). Table 2 provides more detailed information on the demographics of the respondents.

Measure	*Absolute values*	*Percentage values*
Gender	Male Female	41.1 % 58.9 %
Age group	< 25 years 25 – 34 years 35 – 44 years 45 – 54 years > 54 years	24.4 % 38.4 % 21.1 % 7.2 % 8.9 %
Monthly income (net)	0 – 1000 € 1001 – 2000 € 2001 – 3000 € 3001 – 4000 € 4001 – 5000 € 5000+ €	14.4 % 21.1 % 23.9 % 17.2 % 12.8 % 10.6 %
Employment status	Student Jobseeker Employed Self-employed Civil servant Retired	23.9 % 2.8 % 62.2 % 6.1 % 4.4 % 0.6 %
Locale of residence[a]	Urban Rural Invalid	18.5 % 74.7 % 6.8 %
Previous use of OGS apps	Not used previously Previously used	60.8% 39.2%

[a] Classification is determined by the location of the residence within or outside the delivery area. Unserviced regions are classified as rural, while those serviced are classified as urban. Invalid cases could not be classified.

Table 2: Sociodemographic Characteristics of Participants.
Source: Own research, 2024, n = 181.

4. Analysis and Results

The utilization of OGS apps was examined in detail, revealing interesting trends among users. While participants reported using well-known OGS apps such as Flink (26 %) and Gorillas (21 %), the most frequently mentioned app was that of the retailer REWE (35 %) (cf. Figure 3). This indicates a preference for established retail brands in the OGS market, suggesting that traditional retailers may have a competitive advantage in attracting and retaining users through their dedicated apps. In contrast, more minor delivery services such as Wolt (6 %) and Getir (9 %) and niche players such as Bringmeister, Picnic, and Knuspr (1 % each) accounted for a smaller share of reported usage, highlighting their more limited market penetration or familiarity among surveyed users.

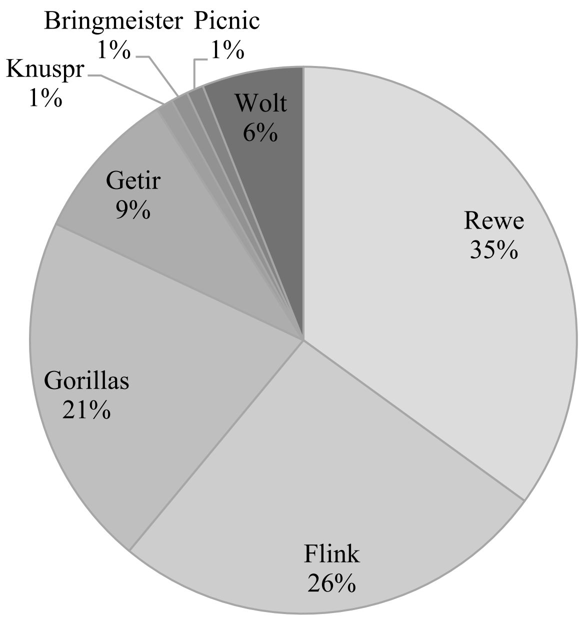

Figure 3: Apps Used by the Respondents.

All survey participants were asked to indicate which devices they preferred for app usage. The majority used smartphones (86 %), but some also used tablets or laptops (9 %), and a notable percentage (5 %) used smartwatches. This highlights the importance of ensuring app compatibility across various devices to meet user preferences and enhance accessibility.

To explore the relationship between these characteristics and the intention to use OGS apps, we performed a statistical analysis of the data using IBM SPSS 28 software. Before testing the proposed research model and its associated hypotheses, the collected constructs were assessed using a maximum likelihood principal component analysis (MLPCA) and evaluated for their statistical quality through reliability tests and descriptive analyses of the scales. An MLPCA is a statistical technique for analyzing a dataset containing intercorrelated dependent variables. The objective is to extract the essential information from the dataset and express it as a reduced number of variables, known as main components. To ascertain the suitability of the data for an MLPCA, the Kaiser-Meyer-Olkin measure (KMO) was employed to assess the adequacy of the sample (Johnson & Wichern, 2007). Bartlett's sphericity test was employed to ascertain the significance of the statements within the dataset. The KMO criterion is calculated from the partial correlations between item pairs. Some authors recommend a minimum value of 0.5 (Backhaus et al., 2015; Cleff, 2015), while others suggest a value of 0.6 (Hartmann & Reinecke, 2013; Tabachnick & Fidell, 2014). The dataset in question exceeded both thresholds, with a value of

0.881. The Bartlett test was employed to investigate the null hypothesis that the correlation matrix was an identity matrix. The p-value was less than 0.001, which was statistically significant, allowing for further analysis (Johnson & Wichern, 2007). Table 3 illustrates the outcomes of the MLPCA, along with the measures of the constructs' reliability (Cronbach's alpha and composite reliability) and validity (average extracted variance). Due to utilizing the UTAUT2 framework, eight components, as described in Section 2, were employed in the factor analysis.

The MLPCA indicated that all UTAUT2 items except HM2 exhibited loadings exceeding 0.6, demonstrating a strong association with the underlying constructs. As Cronbach's alpha values of the HM construct also showed an improvement when item HM2 was excluded, this item was left out from further analysis. The other favorable results can be attributed to the fact that the UTAUT2 is a model that has been subjected to extensive evaluation, and established scales were employed.

Model Constructs	*Indicators*	*Loadings*	*Cronbach's Alpha (CA)*	*Average Variance Extracted (AVE)*	*Composite Reliability (CR rho_A)*
Performance Expectancy (PE)	PE1	0.892	0.912	0.790	0.919
	PE2	0.882			
	PE3	0.893			
	PE4	0.888			
Effort Expectancy (EE)	EE1	0.942	0.948	0.862	0.994
	EE2	0.965			
	EE3	0.960			
	EE4	0.841			
Social Influence (SI)	SI1	0.947	0.949	0.907	0.954
	SI2	0.962			
	SI3	0.948			
Facilitating Conditions (FC)	FC1	0.893	0.863	0.785	0.868
	FC2	0.879			
	FC3	0.884			
	FC4	0.679			
Hedonic Motivation (HM)	HM1	0.911	0.885	0.805	0.973
	HM2	0.900			
	HM3	0.880			
Habit (HA)	HA1	0.874	0.786	0.706	0.871
	HA2	0.543			
	HA3	0.682	no further consideration		
	HA4	0.928			
Price Value (PV)	PV1	0.881	0.912	0.848	0.969
	PV2	0.921			
	PV3	0.958			
Behavioral Intention (BI)	BI1	0.962	0.958	0.922	0.958
	BI2	0.966			
	BI3	0.953			

Table 3: Descriptive Statistics and Tests for Reliability, N = 181.

As evidenced in Table 3, all constructs exhibited values that aligned with statistical quality, as indicated by Cronbach's alpha values exceeding 0.7, AVE (average variance extracted) surpassing 0.5, and composite reliability falling within the 0.7 to 0.95 range as proposed by Lee (2009), Yu (2010), and Hair et al. (2022). Table 4 illustrates the HTMT (heterotrait-monotrait) ratios proposed by Henseler et al. (2015) for evaluating the discriminant validity of variance-based analyses. All HTMT ratios were found to be below the threshold of 0.85, indicating sufficient discriminant validity and confirming the robustness of the measurement model.

	PE	**EE**	**SI**	**FC**	**HM**	**PV**	**H**	**BI**
PE	**0.782**							
EE	0.433***	**0.873**						
SI	0.511***	0.254***	**0.877**					
FC	0.290***	0.556***	0.124***	**0.754**				
HM	0.534***	0.334***	0.490***	0.210***	**0.797**			
PV	0.527***	0.414***	0.288***	0.416***	0.434***	**0.841**		
H	0.597***	0.246***	0.484***	0.183***	0.418***	0.379***	**0.776**	
BI	0.782***	0.352***	0.429***	0.265***	0.480***	0.429***	0.613***	**0.806**

Table 4: Heterotrait–Monotrait Ratio (HTMT); N = 181.

These constructs were then used in multiple linear regression (MLR) to test the hypotheses derived from the adapted UTAUT2 model.

5. Results

Following the formation of the constructs using an MLPCA and the implementation of a series of tests to assess the statistical quality of the collected data, a two-stage, hierarchical MLR was conducted. Other studies have demonstrated that age, gender (Netscher et al., 2024), and previous usage behavior (Frank & Peschel, 2020) influence future BI. Consequently, these criteria were the control variables used in model (0) (Deaux & Lewis, 1984).

In the second step, the study examined the influence of the UTAUT2 components, PE, EE, SI, FC, HM, PV, and HA, on the dependent variable BI. Table 5 illustrates the quality of these models and the coefficient of determination (adjusted R^2). The statistical significance of the change was calculated to ascertain whether the additional variance (R^2) could markedly enhance the model. Model (0) indicates that the control variables accounted for 39.3 % of the explained variance of the main component. In contrast, Model (1), which comprises the seven UTAUT2 constructs, exhibits an explanatory variance of 63.0 %. By combining the control variables with the seven UTAUT2 components, a model was generated that achieved an explanatory variance of 68.8 %. All three models demonstrated statistically highly significant p-values of less than 0.001.

A subsequent multiple regression with a stepwise inclusion of parameters was conducted to ascertain which factors exerted the greatest influence on the modeling of BI. The model exhibited the highest quality with an adjusted R-squared value of 0.694. The key influencing factors were PE, previous use of OGS apps, and HM. This result was corroborated by examining our initial hypotheses (Table 6).

Model	Predictors	adj, R^2	R^2	p
(0)[a]	Control variables	0.393	0.403	<0.001***
(1)[b]	UTAUT 2 construct	0.630	0.644	<0.001***
(2)[c]	Control variables and UTAUT 2 construct	0.688	0.705	<0.001***

[a] Model (0): Predictors = Gender, Age, Previous Use of OGS Apps
[b] Model (1): Predictors = Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit
[c] Model (2): Predictors = Gender, Age, Previous Use of OGS Apps, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit
R^2 = Coefficient determination; *** = Significance of the change [p = 0.001]

Table 5: Multiple Linear Regression: Quality of the Models; N = 181.

Hypotheses	Path Coefficient	Standard Error	Result
H01 PE → BI	0.493***	0.071	✓
H02 EE → BI	-0.012	0.073	x
H03 SI → BI	-0.008	0.062	x
H04 FC → BI	0.019	0.061	x
H05 HM → BI	0.142**	0.070	✓
H06 PV → BI	0.009	0.075	x
H07 HA → BI	0.086	0.082	x
Gender → BI	0.049	0.172	x
Age → BI	0.013	0.008	x
Previous Use of OGS Apps →BI	0.329***	0.101	✓

Note: Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 6: Model Results and Testing of Hypotheses; N = 181

Table 6 illustrates that only hypotheses H01 (performance expectation) and H05 (hedonic motivation) positively influenced BI to use OGS apps. The influence of PE on BI was dominant, with a correlation coefficient of 0.493. This significant positive influence was followed by the control variable previous use of OGS apps, which had a correlation coefficient of 0.329 and was also highly significantly related to BI. Additionally, HM remained a significant predictor of the future use of OGS apps in our study, with a correlation coefficient of 0.142. The remaining predictors of the UTAUT2 model and the control variables, age and gender, could not be proven to be significant estimation parameters in the model. Consequently, these hypotheses had to be rejected.

6. Discussion and Implications for Theory and Practice

This study explored the acceptance and usage patterns of OGS apps in Germany, utilizing the UTAUT2 model to identify key factors influencing user intentions and behavior. This study answers a direct call for future research addressed in Leischner (2023), as the authors posit that OGS in Germany still has a considerable amount of untapped potential, especially with regard to convenience and stress reduction when shopping online. Our study showed that the UTAUT2 model provided a solid framework for understanding the acceptance and usage patterns of OGS apps in Germany. Statistical analysis, including MLPCA and MLR, validated the reliability and accuracy of the constructs that were measured, reinforcing the robustness of the UTAUT2 model. Second, the primary factors influencing the intention to use OGS apps were identified. Performance expectancy (PE), hedonic motivation (HM), and prior use of OGS apps were found to exert the most significant impact. This suggests that users prioritize functional benefits and seek enjoyment and familiarity when engaging with OGS apps, which aligns with the findings from Rudolph et al. (2015). Hedonic motivation is crucial in driving app engagement and sustained use by emphasizing the importance of enjoyment and pleasure. Consequently, users are seeking an experience that is both practical and entertaining. The preference for established retail brands highlights the competitive advantage of traditional retailers in this market. The results of this study provide a clear basis for action for delivery services in the OGS sector in Germany. By considering the challenges of OGS apps and implementing the suggested measures, providers can optimize and increase acceptance of their services.

Theoretical Implications

The study has important theoretical implications for the development of digital services. It highlights the relevance of the UTAUT2 model in understanding consumer behavior relative to OGS apps, emphasizing the importance of PE, EE, and HM. The findings suggest that the UTAUT2 model and the questionnaire need to be adapted to the specifics of OGS applications to accurately represent user perceptions and behaviors. The findings of this study align with previous research that emphasized the importance of PE and HM in technology acceptance (Venkatesh et al., 2012). However, this study extends the existing literature by highlighting the significant role of previous usage behavior, which was less explored in prior research. The emphasis on targeted marketing strategies for repeat customers and operationalizing performance expectations and hedonic motives through user-friendly design and clear value propositions offer new insights to researchers and practitioners. This research also supports the findings of Harborth and Pape (2018), who highlighted the importance of cultural context in technology acceptance. This suggests that future studies should continue to explore cross-cultural differences to gain a more nuanced understanding of user behaviors (Netscher et al., 2024).

Practical Implications

For practice, we suggest focusing the marketing of OGS apps on prior usage behavior, performance expectations, and hedonic motivations. First, it is easier to encourage repeat customers than new customers to use the app, given that they have already had positive experiences with it. Therefore, targeted campaigns should be developed to retain customers and encourage repeat purchases. Second, PE and HM should be operationalized through a user-friendly design and by adding clear value to the app. If the app is both functionally convincing and enjoyable to use, willingness to use it can be significantly increased. Marketing measures should, therefore, focus on improving the user experience and communicating the added value to increase user satisfaction and loyalty.

7. Conclusion and Future Research

The study on OGS apps in Germany provides valuable insights into user acceptance and usage patterns. In conclusion, this study offers valuable insights for both researchers and practitioners in the field of digital services. OGS app providers can optimize their services and increase both user adoption and acceptance by addressing the specific challenges in rural areas and implementing targeted marketing strategies. However, it is important to expand the research scope to include sustainability aspects and potential adverse effects of OGS, which are currently under-explored (Chan et al., 2023) and were not part of this study. Another limitation of this study is the small sample size of 181 participants, which may limit the generalizability of the findings. Additionally, the sample was recruited through social media platforms, potentially biasing the results as not all demographic groups are equally represented. Geographically, the study focuses exclusively on Germany, meaning that the results may not directly apply to other countries or cultures. Additionally, future studies should focus on rural areas and the need for improved logistics and infrastructure.

The data collection was performed over a limited period, from November to December 2023. Consequently, no changes in technology or user behavior that occurred after this period were considered. The reliance on self-reported data introduces the possibility of biases such as social desirability or recall errors that could affect the accuracy of the results. While the UTAUT2 model provided a robust framework for analysis, other theoretical models or additional variables might also be relevant to fully understanding the acceptance and use of OGS apps. Moreover, the study examines the intention to use OGS apps but does not provide a long-term perspective on actual usage behavior and user retention. Focusing on specific predictors such as PE and HM meant that other potentially relevant factors—for example, technological advancements or market trends, like sustainability—were not considered. These limitations provide a framework for future research that could expand and deepen the insights gained from this study. Future research should examine the role of OGS apps in promoting sustainable consumption patterns and supporting local food systems. Future studies can provide a more comprehensive understanding of the complex implications of OGS adoption, balancing technological advancements with sustainability concerns and potential negative societal impacts.

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Appendix

A. 1: QR Code and Link for the Self-created explanatory video that introduced the topic to the participants

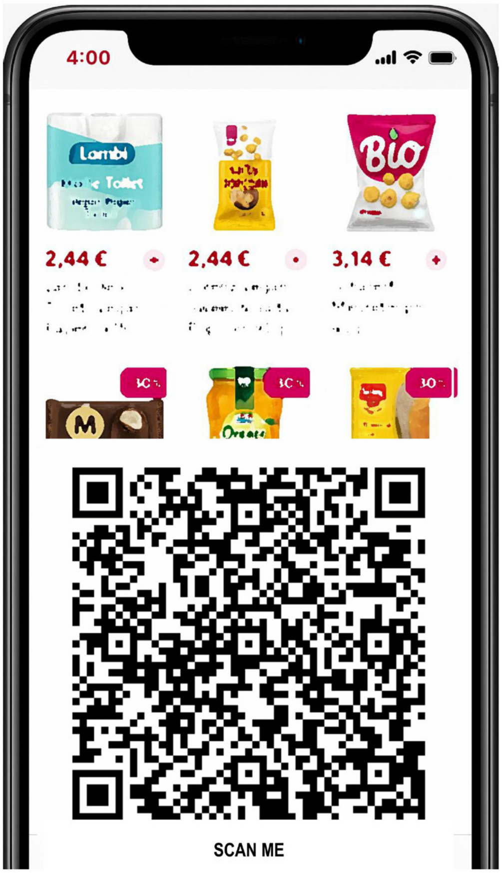

Figure 4: QR code for the explanatory video.

Link for the explanatory video:
https://drive.google.com/file/d/1-KDvolA_mlIWIs_-FckxUdzdkZNQ5vJ6/view?usp=sharing

Digitization Technologies to Ensure Production Conformity

Kerstin Haeckel*, Stephan Husung, Christine Wünsche*****

ABSTRACT

Ensuring production conformity is a growing challenge in the automotive industry. The reasons for this are the increasing number of vehicle variants combined with increasing regulatory requirements in import markets.
Instances of non-compliance with production standards, also referred to as 'Conformity of Production' (CoP), may lead to significant penalties. Today, a partially random and manual assurance process is used in production.
Previous research has shown that automation offers promising potential for improving the CoP process.
The goal is to identify and evaluate an appropriate automation solution for the overall CoP process. The focus of this contribution is on the digitization of the selection process for part IDs and other homologation-relevant labels.
The approach is to apply state-of-the-art evaluation logic to the automated identification of part IDs and homologation-relevant markings in the context of the assurance process in order to identify these markings with the greatest potential for improvement in the automated identification process.
The method with the best prospects of success will undergo initial piloting.

KEYWORDS

Conformity of Production, homologation, automotive, production, manual assurance, assurance process

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1. Introduction

In the automotive industry, marking regulations and requirements are essential to ensure the safety, quality and conformity of vehicles and their parts. These regulations are defined by national and international authorities and structures [1].

Ensuring production conformity in this industry is becoming an ever greater challenge due to the increasing variety of vehicles and the growing demands of import markets.

Each country has its own legal requirements that must be met in the context of "Conformity of Production" (CoP). In Europe, for example, compliance with the "European Regulation 2018/858" is mandatory [2–4].

The CoP refers to ensure compliance with homologated type approval requirements during vehicle production.This process requires the regular assurance that the products manufactured in the series process have the same characteristics and specifications as the vehicle and its parts used for type approval. To ensure this, various assurance measures are performed, including the part identification test.

The part identification test is a procedure within the CoP in which the parts installed in the vehicle are checked to see if they have the same specifications as those in the type of approval documents submitted to the authorities.

At the BMW Group, part identification testing is currently carried out by means of a manual spot check using a paper checklist on the vehicle. The data of the parts on the vehicle is compared with the CoP data to ensure that the parts used comply with the specified standards and thus production conformity is guaranteed. The part identification test is a crucial step in ensuring the quality and safety of vehicles, as well as in promptly identifying potential deviations in the production plant.

Previous work has shown [5] that the part identification number (part ID) did not always meet the legal requirements or was partially illegible, which led to non-conformity in the CoP process. The part identification number is a unique identifier that is assigned to a specific part and is used to uniquely identify it within a system or process [6].

Due to the current manual part identification checks, only a limited number of part IDs or homologation relevant markings are checked, which can potentially lead to incorrect markings going undetected.

Automotive recalls are an industry-wide issue that affects all automakers as they are required to ensure the safety and quality of their products in accordance with regulatory requirements. In the U.S., 331 million vehicles were recalled between 2011 and 2020 due to safety defects and non-compliance. The recall numbers for 2020 and the first half of 2021 do not show a positive trend, but a further worsening [7]. Further statistics on recalls over a time period of two years can be found in Sturm [5].

The numbers show an upward trend, which is due to the increasing amounts of variants as well as the increasing conformity requirements [5].

The results of previous work [5] show that the corrective measures taken so far in the CoP process are not sufficient to achieve a "zero defect strategy" regarding homologation defects. Against this background, measures for automating the assurance process during production are to be investigated.
In essence, there are several technologies for the automated assurance of part IDs or homologation-relevant markings with which the part identification test of the CoP process can be carried out automatically.
A comprehensive investigation into the automated assurance of the CoP process and into which technologies are appropriate for this purpose has not yet been carried out at the current state of the art and is therefore the aim of this contribution.

For this contribution, the following research questions can be derived:
- Which requirements must be met by the technology for part identification within the CoP process?
- Which technologies are appropriate for CoP to automate the part identification process?
- How is the identified technology appropriate for practical application in a real scenario?

2. State of the Art

The analysis of the state of the art is crucial to discuss the current knowledge on "Digitalization Technologies for Ensuring Production Conformity."

This contribution focuses on automating part identification in the CoP process. Section 2.1 describes potentially applicable technologies according to the current state of the art. Here, methods of quality monitoring are examined as they can enable automated part identification and have not yet been applied in the CoP process according to the state of the art.

Sections 2.2 and 2.3 address the state of the art regarding optoelectronic and transmitter-receiver systems. Furthermore, Section 2.4 describes the application of digital quality control in industry, and finally, Section 2.5 conducts comparative studies on digital technologies.

2.1 Digital Object Capture Technologies

Bauer [8] divided the digital capture of objects, such as part IDs or homologation-relevant markings, into three main categories: optoelectronic systems, transmitter-receiver systems, and real-time location systems. These categories were based on different approaches for object recognition.

The first two approaches were primarily focused on the identification of objects. I n contrast, the focus of the third category was on real-time localization of objects, which focused on acquiring location and identification data.

Both optoelectronic systems and transmitter-receiver systems enabled an exchange of information through the transmission of signals and the identification of features with regard to the part ID identification and comparison with the CoP data.

Since this contribution focused on the part identification process, the emphasis was on optoelectronic systems and transmitter-receiver systems. Real-time location systems were not considered in this contribution [8].

2.2 Optoelectronic Systems

Böhmer [9] explained that optoelectronic systems were used to identify objects based on their contours or markings such as colors, reflective marks, fonts, symbols, or bar codes. This was done using optoelectronic reading devices such as laser scanners or cameras, which captured information by illuminating the object with an external light source and receiving the reflected light [10].

Hesse and Schnell [10] report that barcodes are the most widely used concept for marking and tracking objects in logistics. There are different types of barcodes, including 1D, 2D, 3D, and 4D barcodes.

Kern [11] describes an optoelectronic system for character recognition by optical character reading. The efficiency of this technology is highly dependent on the quality of the input documents. In an Optical Character Recognition (OCR) system, an optical scanner first digitises analog documents, identifies text areas, and extracts individual characters. These characters then undergo normalization and noise reduction. OCR thus enables the extraction of inscriptions on parts or images in electronic form for further processing and analysis [11]. extended the functionality of OCR by extracting data from unstructured documents. By incorporating AI technologies, ICR systems improved the recognition of input data, as described in Shidaganti [12].

2.3 Electromagnetic Transceiver Systems

Bauer [8] explains that the exchange of information in electromagnetic transmitter-receiver systems is based on the transmission of signals. The transmitter generates signals that are transmitted by electromagnetic waves. These signals are picked up by antennas on the corresponding objects and transmitted to the receiver.

The receiver then interprets the received signals to reconstruct the transmitted information. Examples for this are Radio Frequency Identification (RFID) [11, 13] and Near Field Communication (NFC) [12, 14].

2.4 Application of Digital Quality Control in Industry

The trade magazine InVision reports about a production conformity assurance process by means of a hand scanner. The content of the label is captured in real time by a hand scanner, and the position of the label is determined. If both characteristics are correct, the device triggers a vibration [15]. The trade magazine InVision reported about a production conformity assurance by means of a hand scanner. The content of the label was captured in real time by a hand scanner, and the position of the label was determined. If both characteristics were correct, the device triggered a vibration [15].

The Volkswagen Group is one of the world's leading automotive companies and uses various technologies for part marking to ensure the quality and traceability of vehicle parts. These include optoelectronic systems (e.g., bar codes), transmitter-receiver systems (e.g., RFID - Radio-frequency identification), and real-time location systems (e.g., GPS - Global Positioning System).The literature reviewed did not describe the use of any technology to ensure CoP identification [16].

The BMW Group's Munich plant relies increasingly on AI for quality monitoring in vehicle production, complementing Smart Data Analytics (SDA) [17] and state-of-the-art measurement technology [18]. Smart Data Analytics is used to analyze large amounts of data using AI and advanced analysis techniques to extract relevant information.

In terms of modern measurement technology, BMW has developed an in-house assurance platform called AIQX (Artificial Intelligence Quality Next) [19] to automate quality processes in production using sensor technology and AI. The platform ensures the quality and completeness of various parts during the assembly process. It is based on intelligent camera systems and sensors along the production line that capture data in real time and analyze it using algorithms and AI.

In the press shop, AI is used to monitor material and process parameters in real time when processing sheet metal panels. This increased transparency and facilitates quality control [20].

BMW and other Original Equipment Manufacturers (OEMs) used RFID technology in their supply chain to track and manage products and parts [21].

In the automotive and food industries, in retail and logistics, barcode and QR code tags were used to ensure product traceability and quality assurance [22–24].

The analysis of the current state of the art shows that a variety of different technologies were already in use in the quality area, but not in the CoP process.

2.5 Comparative Studies of Digital Technologies

In addition, the state of the art has shown that comparisons have already been made between optoelectronic and transmitter-receiver systems [8]. The comparison studies aim to identify the advantages and disadvantages as well as the different application possibilities of these technologies.

The focus of the studies in this contribution is on the automatic identification of the part IDs or the homologation-relevant markings and the subsequent comparison with the homologation data.

Várallyai [23] explains the advantages and disadvantages of the technologies, including their different application possibilities, using the example of an internal changeover from a barcode identification system to a QR code system. In doing so, he gives an overview of different barcode and QR code standards, their printing methods and the way they are read. As a result, it is shown that QR codes are more versatile.

Kulshreshtha, Kamboj and Singh [24] conducted a comparison study of data matrix and QR code on images and increased the level of blurriness for each measurement step. The investigations were related to the decoding robustness of both codes under varying noise levels. The results of the experiments show that the data matrix code is more robust to noise than the QR code and has better decoding performance at the same noise level.

Sivakami [25] conducts a comparison of RFID, barcode and QR code technologies in terms of durability, cost, information capacity and reading range. Each of these technologies basically has advantages and disadvantages, which must be weighed depending on the application. An example of a barcode advantage over RFID is the lower cost. RFID can transmit through objects, allowing multiple tagged objects to be read simultaneously. The reading range of barcodes and QR codes is from a few centimeters to several meters, while RFID can reach several meters. RFID tags are reusable and, unlike barcodes and QR codes, can be modified an unlimited number of times. This is only an excerpt, further advantages and disadvantages can be found in the work of Sivakami [25].

Arendarenko [26] investigated the use of RFID and 2D barcodes and makes several comparisons. RFID showed clear advantages in terms of reading range, storage capacity, reading speed, line of sight independence, and reusability. On the other hand, 2D barcodes are less expensive, less susceptible to electromagnetic interference, and have established standards. The results indicate that both technologies can be used depending on the requirements and conditions of an application.

Brother International GmbH [27] offers a comprehensive overview of the advantages and disadvantages of different barcode, RFID and QR code technologies. The selection of the optimal tracking system depends strongly on the specific application. RFID technology is particularly suitable for identifying groups of goods, tracking high-value products in real time, and dealing with challenging environmental conditions. For simpler and less sophisticated solutions, optical codes such as QR codes and barcodes are appropriate.

In summary, the versatility of QR codes compared to barcodes, the higher decoding robustness of data matrix compared to QR codes and the individual strengths of RFID, barcodes and QR codes depending on the application are to be emphasized. In addition, the higher costs and environmental impacts of RFID technology must be considered, especially when dealing with high volumes of production parts.

The analyzed state of the art does not include a comparison of all these technologies with each other, nor does it reference the CoP process. Therefore, the objective of this contribution is to mitigate this knowledge deficiency.

3. Methodology

Firstly, the methodological approach to selecting a suitable technology is described in Section 3.1 and the structure of the associated sections in this contribution is laid out in Section 3.2.

3.1 Selection of the Methodological Approach

Schuh and Klappert [28] divided the selection of methods into three areas: technology foresight, development planning, and exploitation. These areas represent the phases that a company's technologies go through in order to identify and introduce technologies. Early recognition of new technology focuses on defining the requirement profile and evaluating the various technologies in order to systematically identify an appropriate technology for the CoP process.

Technology recognition is therefore the first important step in automating the CoP process and is therefore the focus of this contribution. This process involves the methodical identification, analysis, and piloting of new and emerging technologies in order to understand their potential for future applications [29].

First, it is necessary to clearly define the criteria for selection based on the requirements from the perspective of the use cases of the technologies and the boundary conditions of the most appropriate technology with a focus on the CoP process. The criteria are divided into technical, economic, social and environmental aspects.

When evaluating technologies for the CoP process, several steps are crucial. The first step is data collection and analysis. This involves gathering the relevant data and information needed to assess the technology. The recognition is done through data analysis and expert interviews. After the necessary information has been gathered, the application of the appropriate methods for the evaluation follows. According to Schuh and Klappert [28], proven methods for early recognition of new technology are argumentation and value benefit analysis [30, 32, 33].

The methods of early recognition of new technology prove to be useful in selecting the optimal approach, comparing technologies, and thus making well-founded decisions. Defining the requirement profile by defining evaluation criteria marks the beginning of early recognition of new technology and is explained in Section 4.

3.2 Structure of the Methodology

In order to provide a clear overview of the structure, Figure 1 illustrates the methodological structure of this contribution.

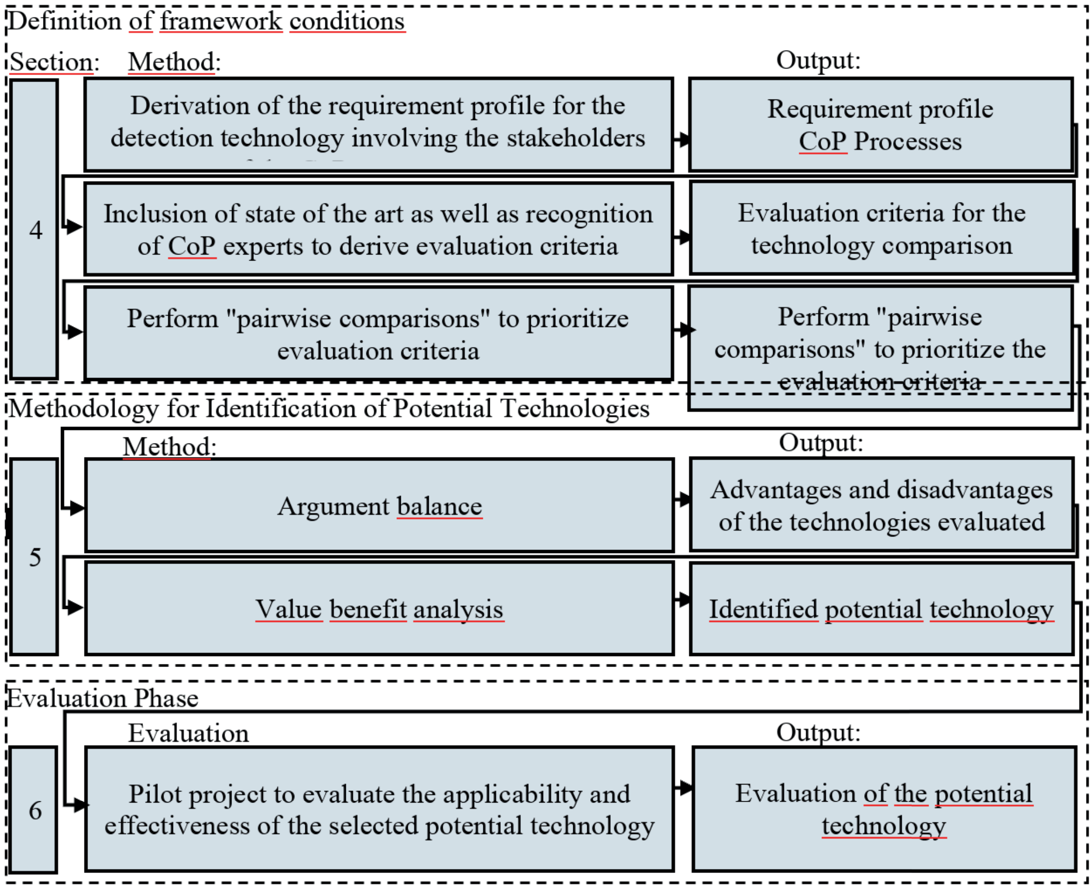

Figure 1: Methodology for technology recognition based on Schuh [30].

This contribution focuses on recognition of new technology (Figure 1). It aims to identify the best appropriate technology for the CoP process through a structured and systematic approach.

At the beginning, a requirement profile for the CoP technology with a focus on the CoP process is defined in cooperation with the stakeholders and the CoP experts of the BMW Group. Based on an analysis of the current state of the art and the previously defined requirement profile, the relevant evaluation criteria are identified together with the CoP experts of the BMW Group. The defined evaluation criteria are compared and evaluated by means of a pairwise comparison to obtain a prioritization.

In Section 5, the advantages and disadvantages of technologies in connection with the CoP process are analysed by means of an argumentation balance.

Finally, a value benefit analysis is performed to identify the potential technology.

Here, the previously defined criteria are weighted and evaluated in order to select the most suitable technology with a focus on the CoP process.

The term "potential technology" refers to the technology that has the greatest potential for process automation in the context of the CoP process [32].

In order to evaluate the practicability of the potential technology, a proof of concept (PoC) is performed in Section 6 [33].

4. Creation of the Requirement Profile and Prioritization of the Evaluation Criteria

In the context of Section 4, the requirement profile for the CoP technology is first established in Section 4.1. In Section 4.2, the current state of the art is analyzed with respect to potential technologies for the CoP process. Based on this analysis, essential evaluation criteria are derived, and the results are summarized in a matrix.

Based on the findings from the requirement profile and the current state of the art, relevant evaluation criteria are derived in Section 4.3. The evaluation and prioritization of the defined criteria is done by a pairwise comparison as described in the following Section 4.4. The creation of the requirement profile is described in Section 4.1.

4.1 Creation of the Requirement Profile by the Stakeholders

The first step in developing the requirement profile is to define the main objective. The next step is to identify the stakeholders who are affected by the automation of the CoP process and who have an influence on the technology. During a workshop with CoP experts, all relevant stakeholders were identified. The following Table 1 provides an overview of the main goal and the defined stakeholders.

Identification of the stakeholders:	**Factory/production facilities:** The transition from manual CoP processes to digitized technology affects the manufacturing process and production flows, which in turn affects the internal operations and employees at the plants.
	Homologation department: The homologation department plays a key role as a stakeholder, as it is responsible for ensuring compliance with homologation regulations. The introduction of a new technology can have an impact on the workflows and requirements of the homologation department.
	National authorities and technical services: National authorities and technical services play a decisive role as stakeholders, as they regulate the CoP process and homologation and set standards. This includes defining the legal framework and regulations that vehicles must meet to be approved for the market. Especially on the Chinese market, the homologation of CoP parts must be listed in a control plan. As part of the annual audit, the authorities check this assurance in production. Any changes to the part safety must be communicated to the authority accordingly [3, 4, 36, 37].
	Suppliers: Suppliers of parts that are components of the homologated product could be affected by changes in the automation of the homologation process. Such changes could impact the requirements for supplied parts.
	Development department: Teams responsible for the development of CoP-relevant products may be affected by the impact of the new technology on the CoP process. Adjustments to development processes and product requirements may be necessary.

Identification of the stakeholders:	**IT department:** The IT department plays an important role as a stakeholder since the implementation of the new technology in connection with the CoP process depends on the support of the IT department. This concerns the integration into different systems as well as other internal processes of the BMW Group.
	Customers: Customers could be indirectly affected by the changes, as homologation standards have a direct impact on the quality and safety of products. Automation could affect the availability and introduction of new products to the market.

Table 1: Identification of the stakeholders.

In a workshop, relevant requirements were defined by a team of CoP experts at the BMW Group with the involvement of the above-mentioned stakeholders. The requirements are presented in Table 2.

Define the requirements:	The technology must be able to flexibly consider all regulatory requirements of the different countries [3, 4, 36, 37]. A concrete example is the Chinese implementation regulation CNCA C11 01:2020, which requires the assurance of up to 300 parts [35]. Therefore, the technology should be able to efficiently inspect a large number of parts with different properties in order to be able to meet the regulatory requirements.
	The BMW Group agrees with its suppliers different limits on the number of defects that are acceptable [38, 39]. The limits are specified in the service specifications agreed between the BMW Group and the suppliers. Due to the critical nature of CoP parts [35], a strict range of 0.001 % (10 ppm) to 0.01 % (100 ppm) was agreed upon between the BMW Group and the suppliers [36]. The technology must ensure that the part marking complies with the CoP data within these agreed tolerances. Within BMW, there is a standard for "quality monitoring using image processing" that must be adhered to. The underlying formula is: ñ ppm × 10 % × 100 % = maximum number of allowable defects. Here, ñ represents the acceptable defect specification limit for the supplier. Thus, maximum allowable error values in the measurement method are from 1 ppm to 10 ppm [38]. For the CoP technology, this value is to be applied to the false-positive identifications. This means that a part with a false ID is nevertheless detected as correct.
	DIN EN 12464-1 (German Institute for Standardization European Norm specifies) [39] that the illumination level in production environments be between 500 and 750 lux [41, 42, 43]. In the BMW Group's production facilities, this value varies between 500 and 850 lux, depending on the day and night shifts [42]. The technology must be able to handle these variations and be usable under different lighting conditions. It should also be scalable to reliably capture part markings on CoP parts of different sizes.

Define the requirements:	The technology had to have an intuitive and user-friendly interface to allow smooth operation by different employees of the BMW Group without the need for extensive training. The user interface should be easy to understand and to navigate to ensure efficient use of the technology. Clear feedback and instructions should be an integral part of the application in order to promote successful acceptance and application of the technology by the staff [43].
	In the production and logistics areas of the BMW Group, various fluctuations in temperature, humidity, dust, dirt and vibration can occur. The production environment in the automotive industry is regulated according to various standards. Section 8.5.6.1.1 of IATF 16949 (International Automotive Task Force) regulates aspects of the production environment [44], while Section 7 of ISO 26262 (functional safety) makes corresponding specifications [45]. A complete avoidance of the mentioned influences is not possible within the production. For this reason, it is necessary that the technology also performs correctly under these influences.
	The need for rapid responsiveness of the technology is to provide near real-time feedback as soon as a CoP deviation is identified. This allows not only the immediate detection of potential violations of compliance policies, but also a rapid response and immediate remediation of the detected deviations [46]. Such rapid response can be achieved through automation. In the automotive industry, the degree of automation refers to the share of automated functions in the overall functionality of a production system. It serves as a measure of a company's equipment with independently operating machines or devices and is expressed as a percentage. A higher value indicates a more advanced level of automation. For example, according to DIN IEC 60050-351 (International Electrotechnical Commission), a system is only called "automated" if its degree of automation is 100 % [47]. Therefore, the requirement for the technology to have a high degree of automation is an important prerequisite.
	The seamless integration of CoP technology is essential to ensure optimal synergies in existing structures. Particularly in the context of the BMW Group, where all homologation data is managed in the central "Approve" database, the technology must be seamlessly embedded in existing IT systems [48]. This enables the efficient exchange of information between different systems, avoids redundancies, and ensures the integrity of sensitive data, especially in official communication. Integration aims to prevent isolated solutions and to integrate CoP technology holistically into the corporate environment.
	The 300 CoP parts [35] are placed at different positions in the vehicle with different distances in the production and logistics area of the BMW Group. The technology must be able to reliably read the part IDs of the CoP parts [35] at different positions, in different material environments and at different distances. This is necessary because a constant distance for reading the part IDs or homologation-relevant markings is not always guaranteed in production. It is important to ensure safety distances in accordance with safety regulations. The spatial requirements and safety standards for production facilities with regard to distances are specified in the European Union's Machinery Directive (Directive 2006/42/EC) [49]. In BMW Group production, the usual distances are between 10 cm and 200 cm [50].

Define the requirements:	Homologation data is highly sensitive information that must be transmitted to the competent authority in accordance with regulations [3, 4, 37]. At the BMW Group, the security and protection of data is a top priority. The European Union's General Data Protection Regulation (GDPR) [51] sets out strict requirements for the protection and processing of data. The storage and archiving of sensitive data sources is regulated by DIN 66399 [52]. It is crucial that the technology complies with the data processing requirements of the GDPR and the archiving requirements of DIN 66399.

Table 2: Define the CoP requirement profile.

The requirements defined for the CoP process include technical, functional, regulatory or other aspects that are critical to the success of the CoP process and technology. The focus is on ensuring that the developed solution meets the actual requirements and expectations of all relevant stakeholders.

The next step is to define the evaluation criteria. These criteria will consider both the stakeholder requirements (Section 4.1) and the current state of the art. The determination of the current state of the art for the evaluation criteria and the derivation of the specific evaluation criteria are described in the following Section 4.2.

4.2 Determination of the Current State of the Art and Derivation of the Specific Evaluation Criteria

In addition to the definition of the requirement profile, research into standard criteria should serve as a reference for the definition of the evaluation criteria.

Rummel's contribution focusses on the evaluation of the suitability of different technologies. Different criteria are discussed, including cost, flexibility, ease of use, accuracy, susceptibility to error, degree of automation, degree of integration, and range [30].

Bauer evaluates technologies with regard to logistically relevant criteria. These are supplemented by usability/application, degree of integration, and security and data protection with regard to the underlying research questions in this contribution [8].

Identification technologies in logistics must meet various operational requirements. According to Hompel, these requirements include ensuring read reliability, sufficient read speed, and read distance [13].

In **Rossouw's** report "10 Factors for the Comprehensive Evaluation of Technologies", essential criteria for the evaluation of new technologies are discussed and considered in relation to autonomous driving. In the automotive industry, especially in the area of homologation, safety and data protection are important [53].

Schuh and Klappert explain how to conduct a value benefit analysis and integrate their research criteria. Some selected aspects are summarized in the present list of criteria, such as "low production costs" and "low investment costs" [28].

Messerle structured criteria for the evaluation of innovations in technical, economic and other effects in order to define a comprehensive overall benefit [54].

Heubach categorized the criteria into several aspects, encompassing functional criteria, operational requirements, design requirements, manufacturing requirements, environmental considerations, measures for environmental impact reduction, testing methods and equipment, market introduction requirements, ergonomic suitability, and economic feasibility [55].

Kröll developed evaluation criteria that include cost, quality, flexibility, and technological maturity [56].

The evaluation criteria identified in the literature largely correspond to the criteria defined in the requirement profile in Section 4.1 and are shown in Table 3 as a summary overview.

	Rummel, 2014 [30]	Bauer, 2019 [8]	Rossouw-Nel, 2019 [53]	Schuh / Klappert 2011 [28]	Messerl, 2016 [54]	Heubach, 2008 [55]	Kröll, 2007 [56]
Cost	x	x	x	x	x	x	x
Flexibility	x	x					x
Usability / application	x		x			x	
Accuracy	x	x				x	x
Degree of automation	x	x					x
Degree of integration	x		x	x		x	x
Range	x	x					
Safety and data protection			x				x

Table 3: Summary of evaluation criteria based on the state of the art.

Together with the previously defined requirement profile and the results of the state-of-the-art analysis, the evaluation criteria are derived. Section 4.3 presents and explains the evaluation criteria.

4.3 Determination of Evaluation Criteria Considering the Requirement Profile and Evaluation Using the SMART Method

This section describes the criteria derived from the requirements and evaluates them using the SMART method to ensure that they are clearly formulated, measurable, achievable, and realistic [57]. The evaluation of these criteria refers to technologies and considers the requirement profile of the BMW Group. The SMART method provides a framework for the precise formulation of measurable and verifiable objectives. The criteria are evaluated based on the five attributes of the SMART method: specific, measurable, achievable, realistic, and time-bound [17, 59]. In this context, the SMART method is used to evaluate criteria and not to set goals. Since the implementation maturity level is still in the distant future, the "time-bound" evaluation criterion is not considered in the evaluation.

Costs [58]
The costs refer to the financial resources required for the implementation of new technologies in the CoP process, including acquisition costs and ongoing operating costs. A clear identification and definition of the costs associated with the implementation of new technologies must be made, with specific metrics defined to evaluate the implementation costs and operating expenses, which are measurable in Euros. These criteria are achievable and realistic if the allowable costs are clearly defined and can be reconciled with the actual costs of implementing the technologies to ensure that they are within the available budget and the implementation is financially feasible. Additionally, the costs are evaluated in terms of the realistic financial capabilities of the BMW Group and the long-term economic viability of the technology.

Flexibility [59]
The new technology must be sufficiently flexible for the future automation of the CoP process to capture the multitude of IDs of different CoP components, including different materials, regardless of material, size, texture, or color (see Table 2: requirement profile). It should reliably function under various lighting conditions, whether natural or artificial, to meet the production requirements of the BMW Group (see Table 2: requirement profile). In the event of changes to the CoP requirements, such as the addition of new features, the technology must be quickly adaptable without disrupting the production line or compromising the capture quality (see Table 2: requirement profile).

Usability / Application [59]
The new technology must have an intuitive and user-friendly interface so that various BMW employees can operate it without extensive training (see Table 2: requirement profile). The specificity of the technology requires that it be designed such that production employees can operate it alongside their regular tasks without causing additional effort. Additionally, the cycle times within the BMW Group must not be extended by the use of the technology (see Table 2: requirement profile). The measurability of usability is evaluated through specific metrics such as the number of steps required to perform tasks with the technology and the time an employee needs to learn and effectively use the technology. The realism of usability is assessed in relation to the actual working conditions and the technical infrastructure of the BMW Group to ensure seamless integration and application (see Table 2: requirement profile).

Accuracy [60]
The technology must operate within defined tolerances to ensure quality monitoring for the homologation of up to 1,500 vehicles per day in the production facilities of the BMW Group [61]. To this end, it is essential to determine a maximum allowable error rate of the technology based on predefined tolerances [37–39] (see Table 2: requirement profile). The Overall Equipment Efficiency (OEE) defines these tolerances [64, 65]. The OEE is calculated based on availability, performance, and quality, and is expressed as a percentage. The BMW Group requires an OEE of over 92 % [64, 65] (see Table 2: requirement profile). The measurability of accuracy is evaluated based on a maximum allowable error rate, an OEE target of over 92 , and the proportion of successfully monitored parts [64, 65]. The achievability of the technology requires that it is capable of maintaining its performance within the specified tolerances (see Table 2: requirement profile). It is important that the technology accurately assigns the component identification and homologation markings. This means correctly identifying both erroneously and accurately marked component IDs. For the CoP technology, this implies that parts falsely identified as correct must be maintained within a stringent tolerance range of 0.001 % (10 ppm) to 0.01 % (100 ppm). The technology must ensure that the part marking complies with the CoP data within these agreed tolerances (see Table 2: requirement profile).

Degree of Automation [47]
The technology must be able to react quickly to deviations in the CoP (see Table 2: requirement profile). Section 4.1 of the requirement profile defines the degree of automation according to DIN IEC 60050-351 [64]. This means that the part ID or homologation marking, especially the precise reading and comparison of the target homologation data, must be carried out in a short time (see Table 2: requirement profile). The measurability of the degree of automation encompasses the number of automatically conducted steps relative to manually performed ones. The feasibility of the requirements for the degree of automation must take into account the actual production conditions and the existing technological infrastructure (see Table 2: requirement profile).

Degree of Integration [65]
The technology to be introduced must be seamlessly integrated into the existing infrastructure of the BMW Group. It is necessary that the technology is compatible with the internal BMW systems and functions without any interruptions or impairments (see Table 2: requirement profile). The measurability of the degree of integration is based on the smooth integration of the technology into the BMW internal systems and the undisturbed functionality after the integration (see Table 2: requirement profile).

Range [66]
The technology must be able to reliably capture the 300 CoP parts at different positions within the production and logistics areas of the BMW Group, while complying with the safety standards for production facilities as outlined in Directive 2006/42/EC [49] and the tolerances defined by the BMW Group [50] (see Table 2: requirement profile). The technology must be capable of reliably capturing the 300 CoP parts at different positions and with varying ranges while adhering to the safety standards of Directive 2006/42/EC (European Union) and the BMW Group tolerances [49] (see Table 2: requirement profile). The measurability of the range is based on the number of successfully captured CoP parts at various positions, compliance with range tolerances, and the number of errors due to insufficient range [50] (see Table 2: requirement profile). The achievability requires that the technology has the technical capabilities to ensure the capture of CoP parts despite varying ranges and positions, meeting the prescribed safety and tolerance standards [50] (see Table 2: requirement profile). The realism of the range requirements must consider the actual conditions in the production and logistics areas to ensure effective implementation of the technology under real-world operational conditions (see Table 2: requirement profile).

Security and Data Protection [67]
The technology must ensure that the results of the CoP selection and data are securely stored after the part ID/marking inspection and comparison with the CoP data to remain meaningful in the event of regulatory inquiries. Given the sensitivity of these data, adequate protection is crucial. When introducing new technologies, it must be guaranteed that the comparison of CoP data with the part is protected against unauthorized access. Similarly, access to the new technology should be granted only to authorized personnel based on the stored CoP data (see Table 2: requirement profile). The specificity requires that the CoP selection results and data are securely stored and protected from unauthorized access, while complying with the requirements of the GDPR [51] and DIN 66399 [52] for the storage and archiving of sensitive data sources (see Table 2: requirement profile). The measurability of the effectiveness of the security measures can be assessed by the number of successfully prevented data protection incidents, compliance with the GDPR and DIN 66399 standards [53, 54] and the number of blocked attempts of unauthorized access (see Table 2: requirement profile). The achievability requires that the technology is capable of implementing robust encryption, secure storage mechanisms, and access controls to protect the CoP data from unauthorized access and ensure the integrity and confidentiality of the data [51] (see Table 2: requirement profile). The security and data protection requirements should be pragmatic and feasible within the existing technological infrastructure of the BMW Group. This ensures effective implementation without disrupting the existing workflows (see Table 2: requirement profile).

The application of the SMART method [57] to the specific criteria of the CoP process, such as cost, flexibility, usability/application, accuracy, degree of automation, range, and safety and data protection, offers a structured approach to evaluate these aspects. The results demonstrate that each criterion is made measurable through clearly defined specifications. Finally, it is necessary to weight the different evaluation criteria. This is described in Section 4.4.

4.4 Pairwise Comparison of Evaluation Criteria Weightings

The previously defined evaluation criteria are now weighted by a pairwise comparison [68].

Subsequently, a percentage is calculated by dividing the sum of the ratings by the number of raters. In this way, the individual criteria are weighed against each other to allow a systematic evaluation by several people. After the comparison, the sums for the respective options are formed and the result is expressed as a percentage. The example of the calculation of "cost vs. flexibility" shows the procedure: the pairwise comparison involved 45 CoP experts. In the survey, 32 people voted 0 and 13 people voted 1. The sum of the ratings is 13, divided by the total number of 45 results in a value of 0.3 (see Table 5). For each evaluation criterion, a sum is calculated and related to the total number. This results in a percentage that reflects the weighting of the metric.

The evaluation was carried out by the BMW Group's CoP expert team, with the average of the individual evaluations serving as the basis for the weighting factor of the value benefit analysis. The survey among all CoP experts was conducted three times with the same group of participants, with the survey being repeated identically in each iteration.

As part of the pairwise comparison of criteria, all CoP experts were presented with identical questions to assess the importance of the criteria. The comparison of criteria was done through a survey. The CoP experts had the opportunity to classify the importance of each criterion using a nominal scale: lower (0), equal (1), or higher (2). A total of up to 37 different questions were to be evaluated in the survey.

An example of a question was: "In relation to the digitization of the CoP process, is flexibility more important, less important, or equally important compared to costs?"
The results of the pairwise comparison is shown in Table 4. Each criterion's importance was calculated by averaging the scores provided by the experts. This average score was then used as the weighting factor in the value benefit analysis.

	Cost	Flexibility	Usability / application	Accuracy	Degree of automation	Degree of integration	Range	Safety and data protection	Total	%
Cost		0,3	0,3	0,4	0,9	0,7	1,3	0,3	4,2	7 %
Flexibility	1,7		0,6	0,4	1,3	1,0	1,7	0,3	7,0	13 %
Usability / application	1,7	1,4		0,57	1,4	1,3	1,7	0,6	8,7	16 %
Accuracy	1,6	1,6	1,4		2,0	1,9	2,0	0,9	11,3	20 %
Degree of automation	1,1	0,7	0,6	0,0		0,9	1,3	0,4	5,0	9 %
Degree of integration	1,3	1,0	0,7	0,1	1,1		1,1	0,3	5,7	10 %
Range	0,7	0,3	0,3	0,0	0,7	0,9		0,1	3,0	5 %
Safety and data protection	1,7	1,7	1,4	1,1	1,6	1,7	1,9		11,1	20 %
								Total:	56	100 %

Table 4: Pairwise comparison of rating criteria weighting.

The values of the individual criteria can be derived from the " pairwise comparison". The most important criteria are "accuracy" and "safety and data protection" with 20 %. The values of the criteria reflect above all the importance of compliance with technical requirements in the area of type approval. Based on the determination of the criteria, the value benefit analysis will be performed in a later step.

5. Methodology for Identification of Potential Technologies

In order to determine the most appropriate technology, an argument evaluation is first performed, taking into account all relevant arguments and aspects, followed by a value benefit analysis, in order to make a final decision based on quantitative data.

5.1 Summary of Arguments for the Discussion of Potential Technologies

The creation of the argument balance [68] is done under consideration of the state of the art and in co-operation with the CoP experts of the BMW Group.

The structure of this balance is based on the categories of optoelectronic systems and transceiver systems. The evaluation of the arguments is shown in Tables 5 and 6, where the different technologies and their identified advantages and disadvantages in the context of the CoP automation are presented.

Techno-logies	Advantages	Disadvantages
	Optoelectronic systems	
QR code	**High data storage capacity** [71, 72]: Can store a large amount of data, including text, URLs, and binary data. CoP assurance process: Allows comprehensive storage of all CoP-related data. **Robust functionality** [71, 72]: QR codes remain functional even if the code is partially unreadable due to damage or contamination. CoP assurance process: According to requirement profile 4.1, the readability and correct matching of the CoP data of all parts must be 100 % guaranteed.	**Challenges of QR code scanning on round and thin objects** [70]: Scanning QR codes on round and thin objects, such as a lambda probe, is often difficult. CoP assurance process: According to requirement profile 4.1, the readability and correct matching of the CoP data of all parts must be 100 % guaranteed. **Coded part identification** [69]: Disadvantage: The part identification is only available in coded form and remains hidden on the part. CoP assurance process: Certain country regulations [71] require that the CoP data must be visibly displayed on the part.

Barcode	**Low dependence on various scanning devices** [71, 74, 75]: Barcodes are compatible with various scanning devices and can be captured and decoded by simple handheld scanners, laser scanners, cameras, and other barcode readers. CoP assurance process: Various scanning devices can be used to read the part marking. **Fast modification of stored data** [69]: Refreshment of stored information CoP assurance process: In case of a change of the component ID / homologation marking data, a fast modification of the stored data is possible with an easy creation of new barcodes.	**Limited data capacity** [71, 74, 75]: Barcodes have a limited capacity of storing information. CoP assurance process: Storage of all CoP-related data is not possible. Limited flexibility [71, 74]: Barcodes contain only numeric data and are less flexible in the representation of information. CoP assurance process: According to requirement 4.1, it must be possible to flexibly read the part identification, regardless of the material, color, size or content of the CoP specifications. **Coded part identification** [69]: Disadvantage: The part description is only available in coded form and remains hidden on the part. CoP assurance process: Certain country regulations [71], however, require that the CoP data must be visible on the part. **Ruggedness** [72]: Sensitivity to external influences. CoP assurance process: According to requirement profile 4.1, the readability and correct matching of the CoP data of all parts must be 100 % guaranteed.
OCR	**Text recognition of printed documents** [71, 76, 77]: OCR enables the precise recognition and extraction of text information on parts. CoP assurance process: In accordance with requirement profile 4.1, the legibility and correct matching of the CoP data of all parts must be 100 % guaranteed. **Extraction of different forms of identification** [71, 76, 77]: OCR can extract different types of information, including text and numbers, from part identifiers. CoP assurance process: The country regulations [71] on the visibility of part markings can be met. OCR can automate the process of data entry. **Applicability to different material**s [71, 76, 77]: OCR can work on a variety of materials, regardless of the surface finish, color or size of the parts.	**Sensitivity to fonts and styles** [71, 77, 78]: This can lead to inaccuracies when reading the part identification. CoP assurance process: In accordance with requirement profile 4.1 (accuracy), the legibility and specific comparison of the CoP data of all parts must be 100 % guaranteed. **Impairment due to poor image quality** [71, 77, 78]: If the image quality is poor, due to any soiling or blurred images, the performance of the OCR technology may be impaired. CoP assurance process: According to requirement profile 4.1 (accuracy) **Limited ability to recognize handwritten text** [71, 77, 78]: OCR specializes in handling printed text and may have difficulty recognizing handwritten or engraved content. CoP assurance process: According to requirement profile 4.1 (accuracy)

OCR	CoP assurance process: See requirement profile 4.1 (flexibility) **Scalability** [71, 76, 77]: The OCR technology can be easily scaled to meet the requirements in different production environments. If different parts place different demands on the OCR technology, for example due to their size, shape or surface, the OCR technology can be adapted to deal with these differences. CoP assurance process: See requirement profile 4.1 (flexibility).	**Dependence on optimal lighting conditions** [71, 77, 78]: OCR systems often rely on optimal lighting conditions, and difficult lighting conditions can affect recognition performance. CoP validation process: According to requirement profile 4.1 (flexibility) **Need for training data** [71, 77, 78]: To achieve accurate results, OCR often requires an extensive training phase with specific data sets, which can mean additional effort. CoP assurance process: according to requirement profile 4.1 (usability).
ICR	**High accuracy (handwritten text recognizable / engraved part identification recognizable)** [71, 79, 80]: ICR can precisely recognize and extract handwritten text and engraved content. CoP assurance process: According to requirement profile 4.1 (accuracy) **Adaptability to different writing styles** [71, 79, 80]: ICR can adapt well to different writing styles and variants, enabling reliable results in text recognition. CoP assurance process: According to requirement profile 4.1 (accuracy) **Improved processing of unstructured data** [71, 79, 80]: Effective at processing unstructured data. CoP assurance process: In accordance with requirement 5.1 (flexibility), there is a requirement that the new CoP technology should be able to process unstructured data. **Integration with OCR for comprehensive text recognition** [71, 79, 80]: ICR can be integrated with OCR technologies to enable comprehensive text recognition for both printed, handwritten or engraved content. CoP assurance process: According to requirement 5.1 (accuracy, level of integration and flexibility).	**Complexity of handling** [71, 80, 81]: Processing handwritten or engraved content as well as different writing styles can be more challenging due to their complexity. CoP assurance process: According to requirement profile 4.1 (flexibility and user-friendliness) **Higher effort regarding requirements for training data** [71, 81, 82]: ICR requires more extensive and specific training data to ensure accurate detection. CoP assurance process: According to requirement 5.1 (accuracy, level of integration and ease of use) **High computing power required** [71, 81, 82]: ICR may require higher computing power, especially if large amounts of handwritten or engraved content are to be processed. CoP assurance process: According to requirement profile 4.1 (degree of Integration) **Costs for implementation and training** [71, 81, 82]: Implementation of ICR technologies can be costly and the training of systems may require additional resources. CoP assurance process: According to requirement profile 4.1 (costs), the cost-benefit ratio of the potential technology should be considered. In relation to training costs, the potential technology should be designed to be intuitive and user-friendly in accordance with requirement profile 4.1 (user-friendliness).

Table 5: Argument balance – optoelectronic systems.

Techno-logies	Advantages	Disadvantages
Transmitter-receiver systems		
RFID passive	**Automation and efficiency** [83, 84]: RFID enables automatic identification of parts without direct visual contact. CoP assurance process: In accordance with requirement profile 4.1, flexible reading of part identification must be possible. **Contactless identification** [83–85]: As passive RFID tags do not have their own energy source, they are activated by the electromagnetic energy of the reader. CoP assurance process: This enables contactless identification of the CoP parts, which meets the requirements of profile 5.1 (flexibility/user-friendliness). **Power supply** [69]: Passive tags do not require their own power source and are therefore maintenance-free in terms of battery replacement or charging. CoP assurance process: In accordance with requirement profile 4.1 (user-friendliness). **More compact dimensions and lightweight design** [83–85]: Passive RFID tags are characterized by their compact and lightweight design, as they do not require their own power source. This makes them particularly appropriate for applications with limited space or weight restrictions. CoP assurance process: In accordance with requirement profile 4.1 (flexibility).	**Costs** [71, 86]: It is necessary to check up to 300 parts [35] for their part IDs or homologation-relevant labels. In the production plants of the BMW Group, up to 1,500 vehicles are produced every day [61]. This means that a total of 300 different parts per vehicle, multiplied by 1,500 vehicles per day, must be tracked. This requirement implies that each individual part must be equipped with a passive RFID tag, which is associated with considerable costs [84]. CoP assurance process: According to requirement profile 4.1 (costs) **Limited reading range** [71, 83, 84]: Passive RFID systems have a limited reading range and may therefore have difficulty identifying multiple items at the same time. CoP assurance process: According to Requirement 4.1 (range) **Coded part identification** [71, 83, 85]: Disadvantage: The part identification is only available in coded form and remains hidden on the part. CoP validation process: Certain country regulations [71] require that the CoP data must be visible on the part. **Reduced data transfer rates** [71, 83, 85]: Passive RFID tags have lower data transfer rates active. CoP assurance process: As per requirement 4.1 (flexibility). **Dependence on external reduced performance in demanding environments** [83, 84]: Passive RFID tags can be affected in areas with high metal content or other interfering materials. CoP assurance process: According to requirement profile 4.1 (error susceptibility/accuracy).

RFID active	**Greater reading range** [83, 84]: Active RFID tags have a greater reading range. This enables the tracking of objects over greater distances. CoP assurance process: According to requirement profile 4.1 (range). **Higher data rates** [83, 84, 85]: Active tags can support higher data transfer rates, which is particularly important in applications with extensive data requirements. CoP assurance process: Complies with requirement 4.1 (automation, level of integration). **Improved performance in metal-rich environments** [83, 84]: Active RFID tags are more powerful in metal-rich environments because they can transmit stronger signals due to their active power source. CoP assurance process: According to requirement profile 4.1 (accuracy, flexibility, and error susceptibility).	**Costs** [81, 84]: Each part must be tagged with a passive RFID tag, which adds significant cost [84]. CoP assurance process: According to requirement 4.1 (cost) **Larger size and weight** [81, 83]: Active RFID tags are larger in size and heavier in weight, making them less appropriate for applications where size and weight play a role. CoP assurance process: According to requirement profile 4.1 (flexibility). **Coded part identification** [69, 81, 82]: Disadvantage: The part identification is only available in coded form and remains hidden on the part. CoP assurance process: Certain country regulations [71], however, require that the CoP data must be visible on the part.
NFC passive	**Integration options** [85, 86]: NFC technology is already integrated into numerous smartphones and other devices, allowing for easy integration. CoP assurance process: Meets requirement profile 4.1 (flexibility and level of integration). **No batteries required** [85, 86]: Passive NFD tags do not require their own power source and are therefore maintenance-free with respect to battery replacement or recharging. CoP assurance process: Requirement 4.1 (usability).	**Costs** [87, 88] Each individual part must be equipped with a tag, which leads to considerable costs [87, 88]. CoP assurance process: According to requirement profile 4.1 (costs) **Low reading range** [86, 89]: Passive RFID systems have a limited reading range and could therefore cause difficulties in the simultaneous identification of multiple parts. CoP assurance process: According to Requirement 4.1 (range) **Reduced data rates** [85, 86]: Passive NFC tags have reduced data transfer rates. CoP assurance process: According to requirement profile 4.1 (flexibility). **Security and privacy** [85, 86, 89]: A potential risk of NFC lies in the fact that unauthorized devices or persons could gain access to transmitted data. CoP assurance process: According to requirement profile 4.1 (security and privacy). **Encoded part identification** [89]: Disadvantage: The part identifier is only available in encrypted form and remains hidden on the part. CoP assurance process: Certain country regulations [71] require that the CoP data must be visible on the part.

NFC active	**No complex configuration required** [85, 86, 89]: See NFC passive. **Integration capabilities** [85, 86]: See NFC passive. **Higher data rates** [89]: Active NFD tags can support higher data rates, which is particularly important in applications with extensive data requirements. <u>CoP assurance process:</u> According to requirement profile 4.1 (automation, level of integration).	**Costs** [87, 88]: Each individual part must be equipped with a tag, which leads to considerable costs [87, 88]. <u>CoP assurance process:</u> According to requirement 4.1 (costs). **Security and privacy** [85, 89]: See NFC passive. Encoded part identification [69, 89]: See NFC passive. **Increased size and weight** [85, 86]: Passive NFD tags are larger in size and heavier in weight, making them less appropriate for applications where size and weight are important. <u>CoP assurance process:</u> According to Requirement 4.1 (Flexibility)

Table 6: Argument balance – transmitter-receiver systems.

The results of the argument balance are used in the following value benefit analysis, which is presented in section 5.2.

5.2 Value Benefit Analysis to Identify Potential Technologies

The purpose of the value benefit analysis is to evaluate different technology variants based on previously defined evaluation criteria (see Section 4.3). The weighting of these criteria is derived from the pairwise comparison (see Section 4.4).

The BMW Group's CoP experts conducted the value benefit analysis, considering the previously prepared argumentation. The benefit analysis is divided into the areas of optoelectronic systems and transmitter-receiver systems. The results are shown in Tables 7 and 8.

Evaluation criteria	WF (%)	Optoelectronic systems							
		QR code		Barcode		OCR		ICR	
		DF		DF		DF		DF	
Cost	4.2	5	20.8	5	20.8	3	12.5	3	12.5
Flexibility	7.0	3	21.0	2	14.0	4	28.0	4	28.0
Usability / application	8.7	4	34.8	4	34.8	5	43.6	5	43.6
Accuracy	11.3	5	56.5	5	56.5	3	33.9	5	56.5
Degree of automation	5.0	1	5.0	1	5.0	5	25.0	5	25.0
Degree of integration	5.7	5	28.6	5	28.6	5	28.6	5	28.6
Range	3.0	1	3.0	1	3.0	5	15.0	5	15.0
Safety and data protection	11.1	4	44.5	3	33.4	5	55.7	5	55.7
Total		214		196		242		265	
Rankings		**5**		**6**		**2**		**1**	

Table 7: Value benefit analysis – optoelectronic systems.

(WF = weighting factor, DF = degree of fulfillment, QR = Quick data encoding, OCR = Optical Character Recognition, ICR = Intelligent Character Recognition)

Evaluation criteria	WF (%)	Transmitter-Receiver System							
		RFID passive		RFID aktive		NFC passive		NFC aktive	
		DF		DF		DF		DF	
Cost	4.2	4	16.6	3	12.5	4	16.6	4	16.6
Flexibility	7.0	4	28.0	5	35.0	3	21.0	4	28.0
Usability / application	8.7	4	34.8	4	34.8	2	17.4	2	17.4
Accuracy	11.3	5	56.5	5	56.5	5	56.5	5	56.5
Degree of automation	5.0	5	25.0	5	25.0	1	5.0	2	10.0
Degree of integration	5.7	4	22.8	3	17.1	2	11.4	2	11.4
Range	3.0	2	6.0	4	12.0	1	3.0	1	3.0
Safety and data protection	11.1	4	44.5	4	44.5	4	44.5	4	44.5
Total		234		237		175		187	
Rankings		**4**		**3**		**8**		**7**	

Table 8: Value-benefit analysis – transmitter-receiver systems.

(WF = weighting factor, DF = degree of fulfillment, RFID = Radio-Frequency Identification, NFC = Near Field Communication)

The partial value benefit values are determined by multiplying the degree of fulfillment (DF) by the weighting factor (WF), where the DF indicates the extent to which a criterion is fulfilled and is rated on a scale of 1 to 5. The weighting factor (WF) originates from the previously conducted pairwise comparison according to Section 4.4, Table 5.

Based on the results, a transparent decision can be made by selecting the variant that provides the highest value benefit. As shown in Tables 8 and 9, the ascending ranking shows the technologies that provide the highest value in terms of the CoP process. ICR, OCR and RFID (active/passive) achieve the highest scores.

The next step is to evaluate the findings from the value-benefit analysis, especially those with the highest scores. The ICR achieved the highest score with 453 points and is therefore the focus of the evaluation. For this purpose, a PoC [33] will be conducted to demonstrate whether the identified technologies can be implemented in practice.

5.3 Conducting Inter-Rater Reliability to Assess Consistency of Results

In the process of evaluating survey results, the same CoP experts were interviewed on the same topics at different time points. To ensure the robustness of the results and minimize the potential effects of random variations or other influencing factors, the scenarios were repeated three times with the same CoP experts.

Subsequently, inter-rater reliability [90] was calculated to quantify the consistency of the evaluations and determine whether the experts tended to agree or diverge. Fleiss' Kappa was used to calculate the inter-rater reliability. Fleiss' Kappa measured the inter-rater reliability when multiple respondents (CoP experts) were involved in the assessment. In this case, Fleiss' Kappa was used to examine the agreement or discrepancies in the evaluations of the CoP experts. It assessed the level of agreement beyond what is expected by chance and provided insight into how well the CoP experts agreed in their evaluations. A higher Kappa value indicated stronger agreement in the evaluations (high inter-rater reliability), while a lower value suggested greater discrepancies between the evaluations (low inter-rater reliability) [90, 91].

Formula 1 displays the Fleiss' Kappa formula along with the computed values.

$$\kappa = \frac{p_o - p_e}{1 - p_e} \qquad \kappa = \frac{0{,}82 - 0{,}34}{1 - 0{,}34} \qquad \kappa = 0{,}73 \qquad (1)$$

(1) Formula: Fleiss' Kappa result for inter-rater reliability.

In the Fleiss' Kappa formula, "Po" represented the observed agreement among the CoP experts. It measured the frequency of actual agreement in their evaluations. "Pe" stood for the expected agreement due to pure chance. It indicated how often agreement was expected purely by chance. The difference between "Po" and "Pe" reflected the level of agreement beyond what is expected by chance and provided insights into how well the CoP experts agreed in their evaluations. In the Fleiss' Kappa formula, the value of "Po" was calculated as 0.82 and the value of "Pe" as 0.34. The Kappa value was obtained by dividing "Po" by "Pe". A higher Kappa value, closer to 1, indicated a higher level of agreement among the CoP experts. The calculated Kappa value of 0.73 suggested a good agreement among the CoP experts. There was solid consistency in their evaluations.

In order to obtain a preliminary assessment of the findings, a piloting was carried out on the best result derived from the utility analysis in Section 6.

6. Piloting of the Results of the Value Benefit Analysis

In the context of the value-benefit analysis (Section 5.2), ICR technology was identified as the most appropriate solution for the automation of the CoP process. In order to evaluate the practicability of this technology, a PoC [33] was performed. The aim was to evaluate the identified ICR technology in a realistic environment.

In the following section, the experimental description of the PoC in Section 6.1 was presented first. The results were then presented in Section 6.2 and discussed in Section 6.3 .

6.1 Description of the Experiment

At the beginning of the PoC, the experimental procedure was first described using a technical flowchart. Figure 2 illustrated the ICR technology flowchart.

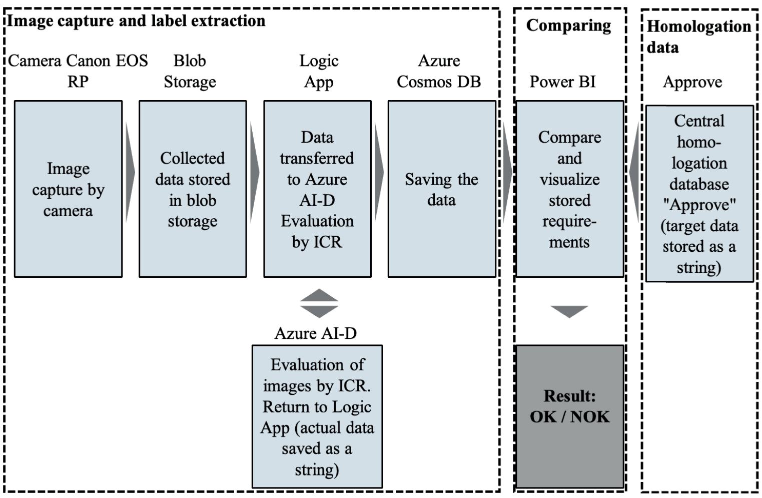

Figure 2: Presentation of the technological structure and the internal BMW tools (flow chart).

The process started with image acquisition using industrial cameras (Canon EOS RP). The collected image files were then stored in a blob storage (cloud storage by Azure). A "Logic App" (BMW internal naming) transferred the data to Azure AI Document Intelligence (Azure AI-D), where an analysis of the images was performed by the ICR. The results of this analysis were sent back to the Logic App. The processed information was stored in an Azure Cosmos DB (Azure Cosmos Database) as a string. This was called string 1. The "Approve" database served as the BMW Group's internal platform for transmitting all homologation requirements to the relevant authorities. The target data for the comparison came from this database. This data was also stored as a string. This was called string 2. In the final step, the stored data was compared to the requirements stored in the Approve homologation database using Power BI (Power Business Intelligence). Using Power BI, all results were marked in order ("OK") / not in order ("NOK"). In the PoC, only OK parts that were correctly marked were used for comparison. This meant that the parts had been correctly delivered by the supplier as well as produced by BMW and that the information in the homologation data matched the respective parts. Therefore, it was checked whether the ICR method marked the images as OK according to the specifications. If the images and their processing led to a result that was not OK, then there was an identification deviation in the technology. Identification deviations were not necessarily caused by a single element of the technological structure, but rather by the interaction of various elements in conjunction with the environment. The framework for the PoC, including the focus, test section, technical parameters, equipment, test series, experiment, and success criteria, was summarized in Table 9.

Framework	
Focus	The goal was to evaluate the ICR technology identified in the benefit analysis (Section 5.2) in a practical experiment. The focus was on the automatic extraction of part IDs and homologation-relevant designations and their comparison with the homologation data. The requirements and limitations from Section 4.1 of the requirement profile had to be considered.
Part	The CoP part identification test involved checking up to 300 different parts [35] for their part ID or homologation-relevant markings (see requirement profile 4.1). Various materials were used, including metal (by means of engraving, stamping, or casting), printed parts (e.g., labels), and plastic or natural and synthetic rubber. The PoC did not investigate all materials but focused on the part with the highest defect rate. Previous studies [5] conducted a statistical analysis of all CoP parts [37] to identify the most common CoP defects. The largest error category concerned tires, with most errors due to incorrect labeling (missing, incorrect, or poorly legible labeling) [5]. The part to be inspected, the tire, came from the manufacturer Pirelli and was made of a mixture of natural and synthetic rubber. The tire was flawless.
Technical parameters of the test part	The BMW Group bought tires from several manufacturers. The problems in the CoP were not specific to one particular supplier. The tire manufacturer was selected for the PoC based on availability. This selection did not represent a piloting of the quality of the manufacturer or its products. Specifications: Pirelli 205/60 R16 96H Tire width: 20.5 cm Tire diameter: 65.2 cm Flank height: 12.3 cm Tread height: 9.2 mm Width: 5.2 mm Character depth: 0.8 mm Character Spacing: 8.9 mm Character or background color: Black Material: Natural and synthetic rubber

Technical parameters of the test part

The focus of the PoC was the marking of tires for the Chinese homologation market. Unlike other CoP parts, the Chinese authorities did not require a part ID specifically for tires. Instead, there was an obligation to verify markings such as tire dimensions, tire diameter, and speed index [35]. The measurement ranges of the parts to be inspected were divided into three different categories. The scope of testing was shown in Figure 3 below:

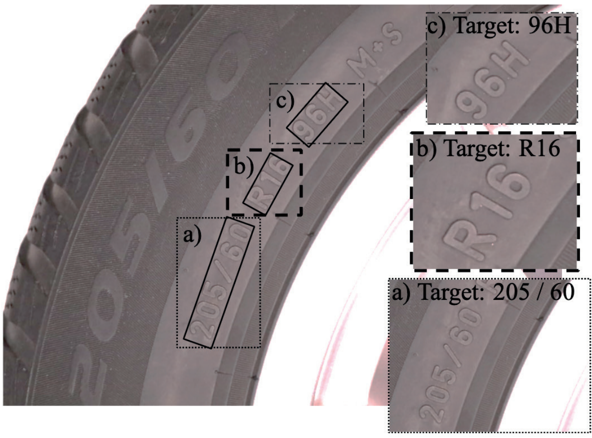

Figure 3: Measuring range of test part.

The indication "205/60" represented the tire dimensions and indicated the ratio between the height and the width of the tire, "R16" the tire diameter and "96H" the load and speed index. These test ranges had to comply with the homologation requirements [3, 4, 34, 35].

Equipment

- Camera (Canon EOS RP + RF 24-105mm F4-7.1 IS STM lens [92]): The camera was operated in automatic mode, which automatically adjusted the exposure time, ISO film sensitivity, exposure compensation, aperture, and shutter speed.
- 2 industrial flashes (SLV 1004076 NUMINOS PHASE [93]): with 10 different settings
- Tripods for mounting lamps and camera
- Lux meter: For measuring brightness (Sauter lux meter SO 200K [94])

Test series Number of measurements

A total of 400 measurements were performed. The design is shown in Table 10.

Experiment

The CoP parts were currently inspected manually on the final vehicle or directly on the production line at the BMW Group plant. In the PoC project, the manual assurance was to be automated by ICR technology. For the implementation in the production environment, it was crucial to ensure a smooth process through the **optimal adjustment of illumination intensity, illumination angle,** and **range**.

Adjustment of illumination intensity:
At the BMW Group, the limits for illuminance in the production environment were specified in Section 4.1 of the requirement profile. According to this standard, the ICR technology had to function perfectly at illumination levels between 500 and 750 lux [40], [41]. In the PoC, an attempt was made to reproduce the real production conditions as accurately as possible. For this purpose, two industrial lamps [93] used to simulate the illumination level in a production environment.

	To achieve a brightness range between 500 and 750 lux (for day and night shifts and different lighting levels in production), ten different lighting levels were alternated. One lamp was mounted at a height of 80 cm and the second lamp at a height of 55 cm to achieve the desired illumination. Optimal illumination was essential because tire assurance involved several criteria, such as 205/60 tire dimensions, R16 for tire diameter, and 96H for speed index.
	Illumination angle (compare α1 and α2 in Figure 12): In the PoC, the illumination angles were set such that the illuminance was within the requirement profile (see requirement profile 4.1). The goal was to match the illumination angles to the real production conditions. For Lamp 1, at a height of 80 cm, the illumination angle was 61°, and at a height of 55 cm, the illumination angle was 47°. For Lamp 2, the illumination angle was 46° at a height of 80 cm, and 31° at a height of 55 cm.
Experiment	**Range:** The 300 CoP parts [35] were placed at different ranges in the production and logistics areas of the BMW Group. The ranges were determined according to the safety and production distances from section 4.1 of the requirement profile [50]. The camera was positioned within a range of 70 cm to fulfill the requirements specified in the range of 10 to 200 cm as outlined in the requirement profile. The ranges from the measurement area to Lamp 1 and Lamp 2 were set to 33 cm and 65 cm, respectively.
	Approve Database: The Approve Database served as an internal BMW platform for the transmission of all approval applications to the responsible authorities. The target data for the comparison was taken from this database, and all results (OK/NOK) were visualized using Power BI.
	ICR-Technology: In the PoC, the ICR technology was based on a Microsoft Azure architecture [95, 96]. The technological process was shown in the flowchart in Figure 2.
	Storage Location: Azure Cosmos DB: BMW used Azure Cosmos DB [96] internally as a database for Microsoft Azure architectures. This NoSQL database from Microsoft allowed the flexible storage of data in different formats such as JSON, BSON, and others. In this PoC, the data was stored in a JSON file within the Azure Cosmos DB.
Success Criteria	In requirement profile 4.1, the identification error was defined according to the standard "quality control by means of image processing" [38]. Thus, the identification error could vary from 1 ppm to 10 ppm. The PoC analyzed how many part IDs were recognized correctly and incorrectly when the illumination intensity and angle were varied. The percentage found was compared to the defined limits to get an idea of whether the technology in the PoC could reach production readiness. The goal of the test was to verify that the ICR method marked the images as in order **(OK)**. If the images and their processing led to a not in order **(NOK)** result, this indicated an identification deviation in the technology. **Explanation of OK/NOK:** • **OK:** The method correctly detected and compared all part information (string 1 = string 2). • **NOK:** String 1 was not equal to string 2, which may indicate an identification error.

Table 9: Experimental description of the piloting.

To determine if the technology had limitations, tests were performed in a range from low illumination (approximately 30 lux) to high illumination (approximately 850 lux). This range was achieved by varying the lamp settings and the lamp height. Two lamps were used for illumination. Preliminary tests had shown that with setting 1 and a lamp height of 80 cm each, a lower lux range was possible. At setting 10, both lamps achieved a high illumination of over 850 lux. The corresponding values were shown in the test plan in Table 11.

During the experiment, several factors were examined. Among them were the variation of the lamp heights (55 cm and 80 cm), which resulted in four different lamp variations, and the adjustment levels of the lamps (10 levels). With the applied design, 400 measurements were made (4 adjustment variations x 10 adjustment levels for Lamp 1 x 10 adjustment levels for Lamp 2). The tests were carried out on a tire with the specification 205/60 R16 96H. A summary of the parameters was given in Table 10.

Lamp height variations	Brightness setting levels Lamp 1	Brightness setting levels Lamp 2	Tire specifications
55 cm / 55 cm	1 2 3	1 2 3	205 / 60 R16 96H
55 cm / 80 cm	4 5	4 5	
80 cm / 55 cm	6 7 8	6 7 8	
80 cm / 80 cm	9 10	9 10	

Table 10: Piloting, test variations of the experiment.

The schematic of the experiment is shown in Figure 4.

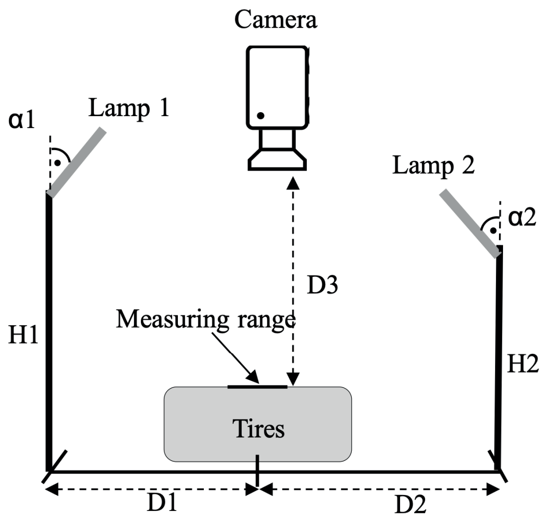

Figure 4: Schematic representation of PoC.

α 1 / 2	Illumination angle
H 1 / 2	Height of lamp
D 1 / 2	Range from lamp to part

The real experiment was shown in Figure 5.

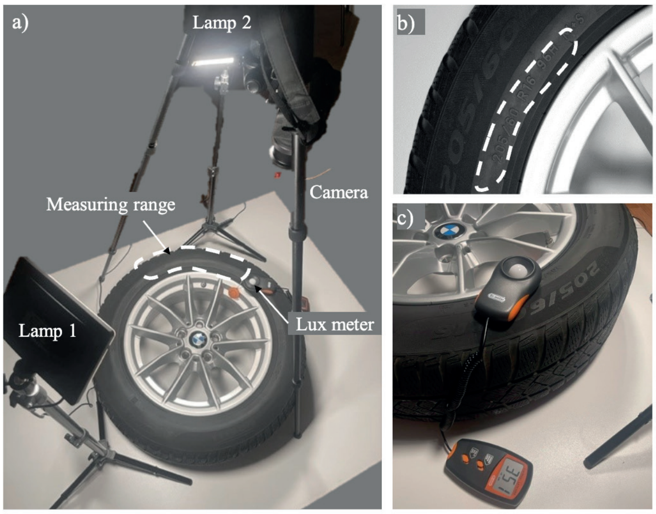

Figure 5: Real experiment of the PoC.

Figure 5 a) showed the overall view. Under b), the measurement range (205/60, R16, 96H) was encircled. In area c), you could see the lux meter for measuring different light levels.

6.2 Results of the PoC

The results of the PoC were shown in the following figures. An experiment was performed with a total of 400 results (OK/NOK). Illumination ranged from 30 to 925 lux. Figure 6 showed an example of image brightness at three different illumination levels over the full range (a, b, c).

Figure 6: Sample images at different levels of illumination.

a)	030 lux
b)	442 lux
c)	925 lux

The production lighting at the BMW Group was typically between 500 and 750 lux [42]. The variance of the illumination level was used to test the influence on the selection quality of the technology. Figure 6 a) showed a low image illumination of 30 lux. Figure 6 b) was approximately in the middle of the illumination levels with 443 lux, which made it easier for the human eye to recognize the measuring range, while 850 lux (Figure 6 c) led to high illumination. The focus was on investigating whether different illumination levels had a positive or negative effect on the selection result.

Figure 7 showed an OK/NOK comparison of the 400 tests performed using illuminances ranging from 30 to 925 lux.

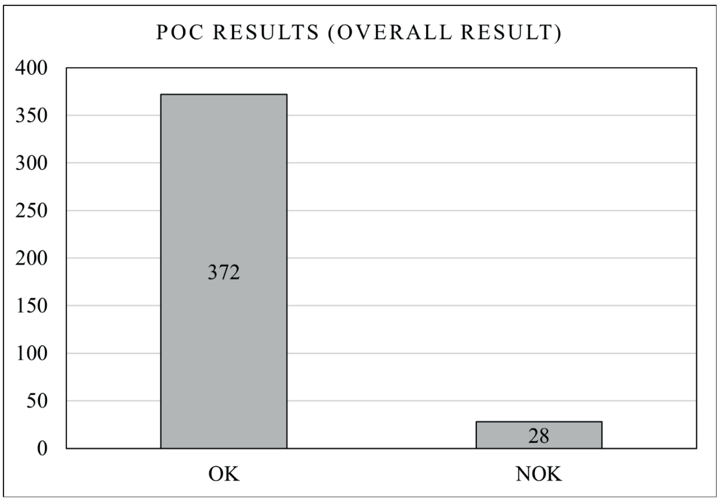

Figure 7: PoC result over the entire lighting value range (30 lux to 925 lux).

It was seen that the ICR technology correctly identified 372 of the CoP parts. However, the ICR technology caused identification errors for 28 parts by interpreting them as "NOK" when in fact they were correct. This represented an identification error rate of 7%. The following analysis was based on the 28 parts where the ICR technology caused an identification mismatch during readout. Figure 8 showed the identification errors that occurred at illumination levels ranging from 30 lux to 925 lux.

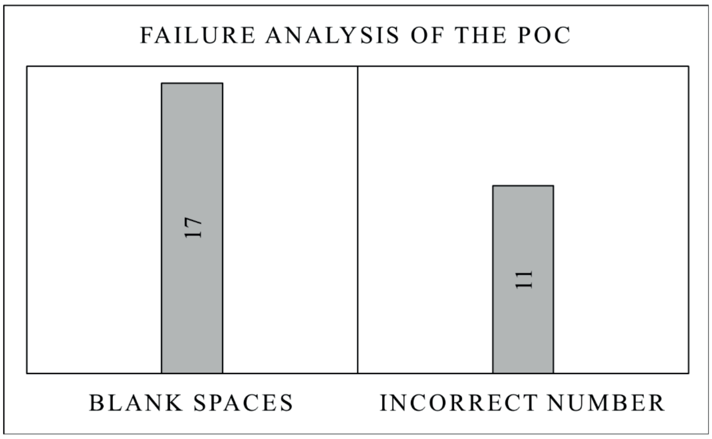

Figure 8: PoC identification deviation analysis over the entire lighting value range (30 lux to 925 lux).

The analysis revealed two categories of identification discrepancies. In 11 cases, the ICR technology misidentified numbers, while in 17 cases it misinterpreted spaces. Figure 9 showed an example of the "wrong number" category, while Figure 10 showed examples of the "space" category.

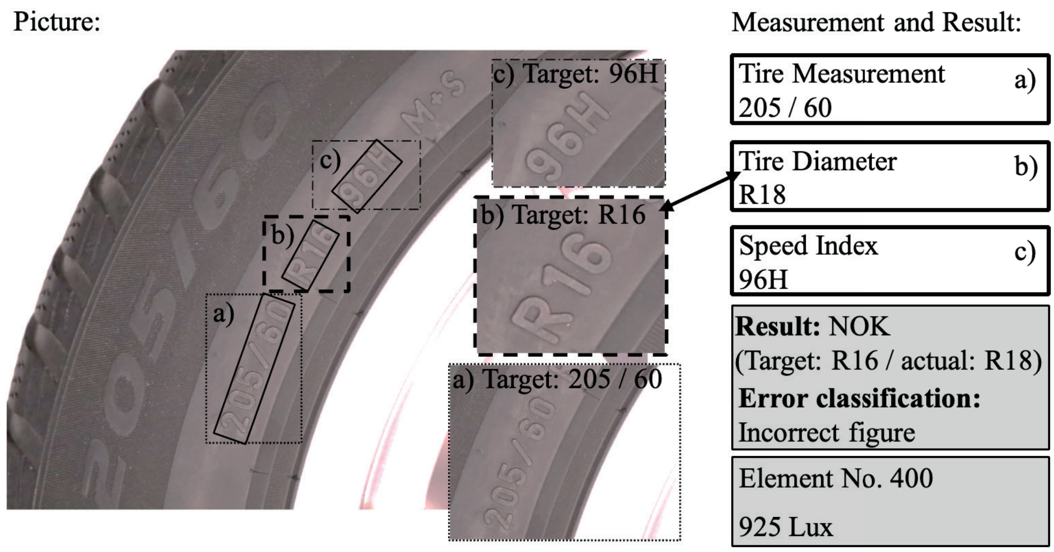

Figure 9: ICR-technology – incorrect figure (target: R16 / actual: R18).

In Figure 9, it was seen that the ICR technology identified the area b) for the tire diameter as R18 instead of R16 (target). An ICR technology identification error occurred in the range of 925 lux. Figure 10 showed the "Blank" category of identification error.

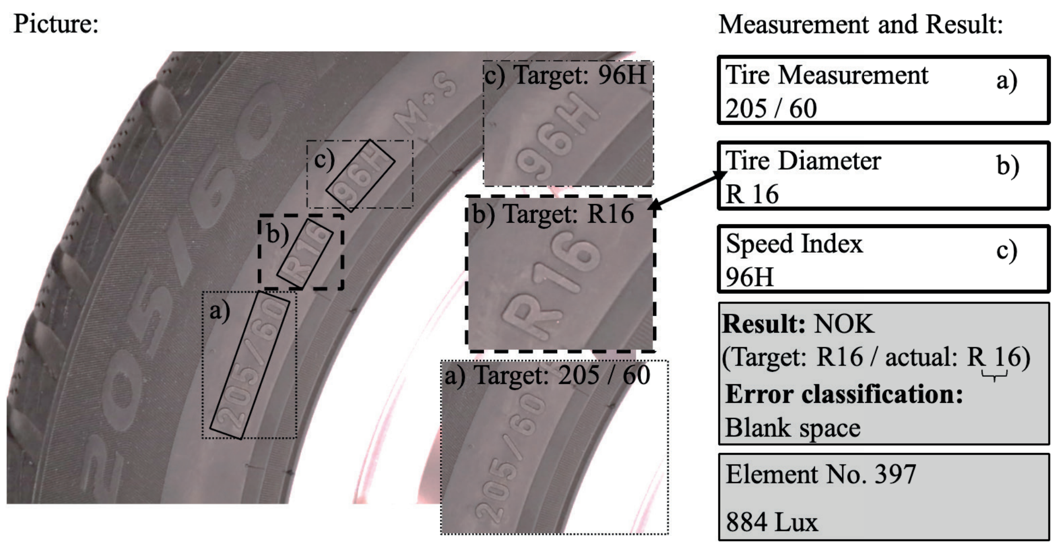

Figure 10: ICR technology – „blank space“ (target: R16 / actual: R16).

At an illumination level of 884 lux, the ICR technology detected and interpreted an additional blank space in area b) for the tire diameter "R16".

The piloting of the 400 results also included an analysis of the behavior of the ICR technology in the illumination range under production conditions (see requirement profile – 500 and 750 lux). These results were shown in Figure 11.

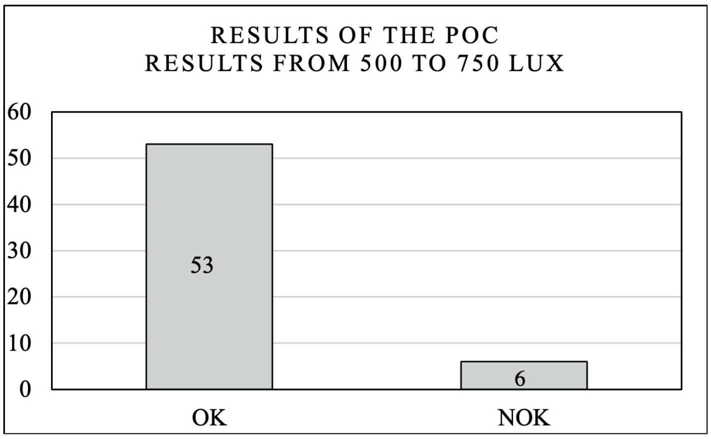

Figure 11: PoC result for the value range 500–750 lux (production conditions BMW Group).

The ICR technology correctly identified 53 of the 59 parts. However, in 6 cases, parts were declared "NOK" when they were in fact correct. This represented an error rate of 10.2%.

The following analyses focused on the 6 parts where the ICR technology caused identification errors during readout. The classification of ICR errors at illumination levels from 500 to 750 lux was shown in Figure 12.

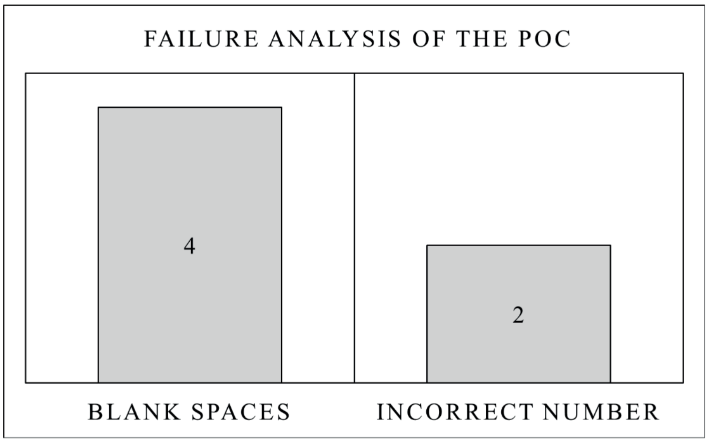

Figure 12: Identification deviation analysis over the value range of 500 to 750 lux (production conditions BMW Group).

The same categories of identification errors occurred as in the overall analysis (see Figures 7 and 8). The ICR technology misidentified numbers in two cases and misinterpreted spaces in four cases. Examples of the identification error categories were shown in Figure 9 ("wrong number") and Figure 10 ("space"). These 6 identification errors occurred within the illumination levels of 665 to 722 lux.

The next step was to analyze the potential causes of the identification discrepancies using ICR technology. Not only was the nature of the discrepancy investigated, but an attempt was made to identify patterns among the discrepancy cases. Particular attention was paid to the analysis of illumination levels to determine if specific lighting conditions affected the accuracy of the ICR technology. In conjunction with this, an analysis of the adjustment levels of the different lamp variants was also performed.

Figure 13 showed a piloting of the ICR technology's identification error in relation to the different illumination levels.

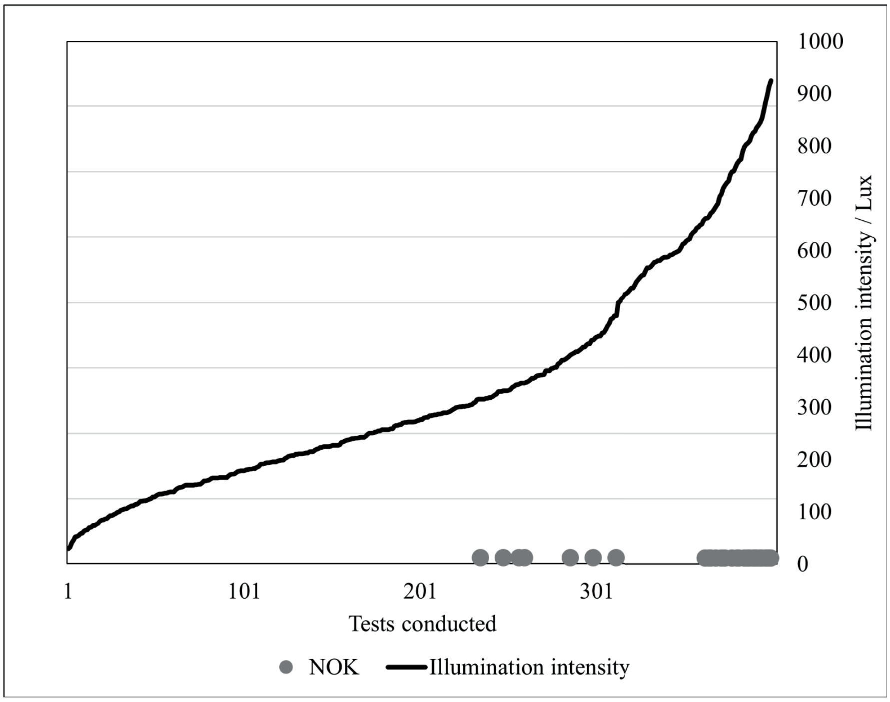

Figure 13: Statistical analysis of ICR technology identification errors related to illumination levels (lux).

The statistical results of the identification discrepancies with respect to the ICR technology showed that an increase was associated with a higher lux range. Up to 316 lux, there were no ICR discrepancies. More ICR discrepancies occurred in the 650 to 925 lux range.

Figure 14 showed a statistical piloting of the identification deviations in relation to the adjustment levels of the different lamp variants. The gray bar indicated the parts read as "OK" using ICR technology, while the red bar indicated the parts read as "NOK".

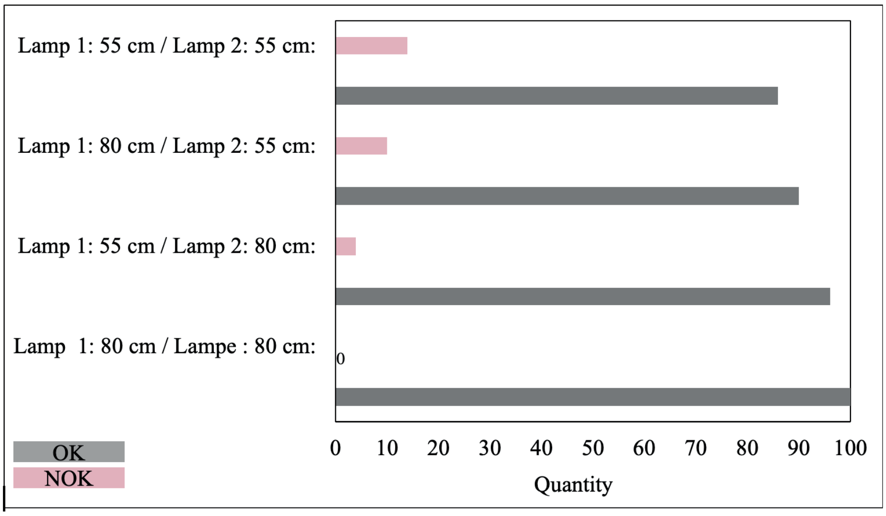

Figure 14: Statistical piloting of the ICR technology's identification deviations
in relation to the lamp variations (Lamp 1 / Lamp 2 [cm]).

The piloting of the ICR identification deviations associated with the lamp variations was performed for the four different lamp settings as explained in Section 6.1, Table 11. The lamp settings 55/55, 80/55, and 55/80 showed ICR identification deviations. There were no identification biases at the 80/80 setting. It was noteworthy that most of the discrepancies occurred when the lamp setting was close to 55/55.

The following section discussed the results of the PoC.

6.3 Discussion of the PoC Results and Further Outlook

The results showed that the ICR technology worked, but not with the desired reliability. Since all parts were correctly marked during the PoC, these identification deviations resulted in a still needed manual step for the production workers, who had to perform additional visual checks to verify the marking.

During the PoC, there were two main identification deviations: first, the ICR technology incorrectly recognized the number, and second, it incorrectly interpreted voids as deviations. Blank spaces were not considered an official CoP discrepancy [2], [3], [4], so the ICR technology needed to be fine-tuned, especially when dealing with blank spaces. An example of such "blanks" was shown in Figure 10.

One focus was on the ICR identification variations as a function of illumination levels (lux). In particular, there were more ICR discrepancies in the 650 to 925 lux range (see the statistical analysis in Figure 13). This could be due to the increased occurrence of glare problems in images with higher lux values, leading to misinterpretation of certain numbers. This relationship was illustrated by the identification bias plots in Figures 9 and 10.

Another focus was on the ICR identification differences in relation to lamp variations (Lamp 1 / Lamp 2 [cm]). At the 80/80 setting, however, no identification deviations occurred. It was noticeable that at the close lamp setting of 55/55 the highest number of identification deviations occurred (see statistical piloting in Figure 14). Possible reasons for this could be the more intense light emission in this area, which could lead to over-illumination and reflections, thus affecting the recognition and interpretation by the ICR technology. Another possibility was that the specific light conditions of this setting might emphasize or diminish certain features of the parts, leading to misinterpretations.

It was necessary to perform a more in-depth analysis to understand the causes of the two types of identification errors (number error and void error) in ICR technology.

Since the ICR technology provided good results especially at low lux levels, possible solutions could include adjusting the lighting conditions, e.g., by targeted dimming. Further optimization could be achieved by fine-tuning the ICR technology, particularly in the handling of gaps, to improve the selection quality.

The PoC was conducted within the BMW Group under the given production conditions and processes. The aim of the PoC was to provide an initial assessment of the ICR technology. However, further investigations were necessary to evaluate the different CoP parts, optimize the technology, and assess other technologies identified in the utility analysis. Furthermore, ensuring a certain level of reproducibility was also crucial. These points constituted the objective of further scientific research.

7. Summary and Outlook

The increasing variety of vehicle variants and the more stringent regulatory requirements in the automotive industry pose a growing challenge for ensuring production conformity [1, 2]. Previous studies [5] have shown that part IDs or homologation-relevant markings do not always comply with legal standards, as manual spot checks cover only small quantities. Recall actions affect all automotive manufacturers who must ensure safety and quality according to legal requirements.

The aim of this contribution is to identify and evaluate an appropriate automation solution for the homologation process. The focus is initially on digitizing the reading process for part IDs and homologation-relevant markings. Sections 4 and 5 of the CoP technology analysis include an investigation of the CoP process. In section 4, a requirement profile is created, and the current state of the art is analyzed. The results are used to derive evaluation criteria, which are evaluated and prioritized using a pairwise comparison. In this pairwise comparison, the CoP experts had to assess the different criteria multiple times through a survey to determine their importance. The results of the criterion prioritization were presented in the pairwise comparison, which in turn influenced the benefit analysis.

Section 5 captures the advantages and disadvantages of technologies in the CoP process, followed by a benefit analysis to identify the optimal technology. The structure is based on the categories of optoelectronic and transmitter systems.

The results from the pairwise comparison, argument balance, and benefit analysis indicate that technologies such as ICR, OCR, and RFID have been identified as potential technologies for securing the CoP process. Therefore, further evaluations on practical application will exclusively focus on these technologies.

The initial practical evaluation of the ICR technology in Section 6 served as an initial assessment, but further analyses with appropriate statistical evaluations need to be conducted. Hence, the results provide an initial assessment but should not be generalized.

The practical evaluation of the different technologies in conjunction with the CoP parts, as well as the analysis of when the technology can be implemented in the BMW product development process, represent further research potential.

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List of Abbreviations:

AI:	Artificial Intelligence
AIQX:	Artificial Intelligence Quality Next
CoP:	Conformity of Production
DB:	Database
DF:	Degree of Fulfillment
DIN EN:	German Institute for Standardization European Norm
GDPR:	General Data Protection Regulation
GPS:	Global Positioning System
IATF:	International Automotive Task Force
ICR:	Intelligent Character Recognition
IEC:	International Electrotechnical Commission
OEMs:	Original Equipment Manufacturers
OCR:	Optical Character Recognition
OEE:	The Overall Equipment Efficiency
part ID:	Part Identification Number
PoC:	Proof of Concept
ppm:	Parts per Million
RFID:	Radio Frequency Identification
SDA:	Smart Data Analytics
WF:	Weighting Factor

Improving Customer Experience Using Smart Technologies in Smart Stores

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ABSTRACT

This study investigates how ethical aspects, safe technology, and customer-friendly technologies influence the customer experience in smart stores. Smart stores are unmanned retail stores that integrate smart technologies and services. An empirical model was proposed and validated using exploratory factor analysis and multiple regression analysis, with n = 402 participants. The results demonstrate that all three constructs have a positive influence on the customer experience in smart stores. However, the results also suggest that store-based interactions (e. g. seamless access and a safe environment) have a stronger influence than product-based interactions. The results highlight the need for retailers to prioritise smart technologies that visibly enhance safety, usability, and ethical transparency. These insights support the development of smart stores that foster customer trust, improve interaction quality, and strengthen long-term customer relationships.

KEYWORDS

Smart store, customer experience, smart technologies, safe technology, ethics, customer-friendly technology

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1. Introduction

The retail sector is confronted with considerable challenges, particularly in terms of staffing shortages and pressure to maintain profitability (Grewal et al., 2023). These challenges have intensified in recent years due to a tightening labor market and increasing demands for operational efficiency (Benoit et al., 2024). Considering these developments, the implementation of smart stores represents a forward-looking response (Netscher et al., 2025). Smart stores are unmanned physical retail stores that rely on smart technologies and services, frequently based on Internet of Things (IoT) and Artificial Intelligence (AI) (Chen & Chang, 2023). Recent regulatory changes, such as court rulings permitting extended opening hours (e.g., in Hesse, Germany), are increasingly enabling the operation of smart stores and highlight the growing relevance of this retail format (Schumacher & Rüschen, 2023).
Existing research has examined the acceptance of smart stores, often drawing on established models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Netscher et al., 2025; Park & Zhang, 2022). These studies analyse constructs such as perceived usefulness, ease of use, and technology anxiety, providing valuable insights into consumers' willingness to adopt smart stores. Additionally, several studies have examined the perceived value of smart stores by considering utilitarian motivations, such as time efficiency and convenience, and hedonic motivations, such as enjoyment and novelty (Chang et al., 2023; Chen & Chang, 2023).

However, smart stores are progressively incorporating sophisticated smart technologies, such as computer vision, which gives rise to new concerns (Jordan et al., 2023; Jordan et al., 2025). In particular, the role of ethical considerations, perceived technological safety, and customer-friendly technologies remains underexplored (Agbese et al., 2023); and limited research exists on how these concerns influence the customer experience (Benoit et al., 2024).

To address this research gap, the present study builds upon the conceptual framework by Tiutiu & Dabija (2023), which emphasises the importance of safe and ethical technology in smart retail environments. The aim is to explore how these factors shape customer experiences in smart stores and to derive practical implications for retailers. Therefore, the study addresses the following research question: *How do ethical aspects, safe technology, and customer-friendly technology influence the customer experience in smart stores?*

To answer the research question, an empirical model was developed and validated using explorative factor analysis and multiple regression. Section 2 outlines the theoretical basis of the study. Section 3 outlines the development of the hypothesis, and Section 4 describes the methodology. The findings are presented in Section 5. Section 6 discusses the academic and practical implications. Section 7 contains the limitations and future research directions, while Section 8 concludes the study.

2. Literature Review

2.1 Smart Stores

Smart stores are unmanned retail environments that rely on smart technologies and smart services, often based on the IoT and AI, to optimise shopping processes and enable autonomous store operations (Chen & Chang, 2023). Although a universally accepted definition of smart stores is still lacking, the integration of smart technologies and services is widely recognized as a defining characteristic in the academic discourse (Benoit et al., 2024). Central to this understanding is the creation of an immersive in-store customer experience enabled by smart technologies (Alexander & Kent, 2022). The term "smart" refers to the interconnection of those smart technologies to enhance operational efficiency and improve customer experience (Adapa et al., 2020). The degree of smartness within a store is reflected in its implemented smart technologies, which can be divided into front-end and back-end services. Front-end technologies, such as interactive displays or seamless checkout, directly shape the customer experience (Fan et al., 2020). In contrast, back-end technologies support internal operations, such as inventory tracking, but remain invisible to customers (Shankar et al., 2021).

The shopping journey usually starts with customer authentication at the store entrance. Customers scan either the store's mobile app or a registered credit or debit card at an entry terminal to facilitate a seamless transition into the shopping environment (Benoit et al., 2024).

Smart shelves enhance traditional shelving systems by using radio frequency identification (RFID) technology to enable precise, real-time inventory management (Zhu et al., 2018). RFID technology enables the continuous tracking of product locations and customer interactions within the store. When customers select items, they are automatically recorded and added to a virtual shopping basket (Chen & Chang, 2023). Payment is processed via a seamless checkout system (Jordan et al., 2023). This automated procedure charges the virtual shopping basket upon the customer leaving the store, with the corresponding amount debited from a pre-registered payment method, thus rendering the traditional checkout process obsolete (Netscher et al., 2025). Although this system increases operational efficiency and reduces transaction time, it may also lead to a reduced sense of control and transparency for customers, particularly given the novelty of the system and limited user familiarity with such technologies (Riegger et al., 2021).

Research into the acceptance of smart stores has already examined factors such as expectations and influencing conditions, particularly through established acceptance models (Netscher et al., 2025; Szabó-Szentgróti et al., 2023). These studies indicate that smart stores are generally accepted by customers. Building on this, empirical studies have shown that customers value the utilitarian benefits of smart stores, such as time savings and increased efficiency, as well as the hedonic benefits, such as the entertainment and novelty they offer (Chang et al., 2023). Further research has identified specific motivational factors that reinforce the intention to use. Perceived usefulness and perceived enjoyment have emerged as key factors that positively influence the intention to use smart stores, provided customers feel sufficiently technology-ready (Chang & Chen, 2021). Due to the novelty of smart stores the customer experience in this context has not yet been examined with regard to ethical and safe technology-related aspects. However, existing studies in related fields, particularly those focusing on the customer experience with AI in online retailing, have already incorporated constructs such as ethical considerations, safe technology and user-friendly technology (Tiutiu & Dabija, 2023). While these findings cannot be transferred directly to smart stores as physical retail stores, they clearly highlight the need for empirical research on these constructs within the context of smart in-store experiences.

2.2 Customer Experience (CX) in Smart Stores

Customer experience (CX) is an integral part of marketing and retail research (Lemon & Verhoef, 2016). CX is defined as customers' internal and subjective responses to any direct or indirect contact with a company, including technological interactions within a retail setting (Lemon & Verhoef, 2016). Previous studies have identified four aspects of CX: (a) cognitive (b) emotional, (c) physical and sensorial, and (d) social elements. Customer-friendly technologies are particularly concerned with the cognitive aspect of CX (Ameen et al., 2020). They support information processing, promote an understanding of products and services, and thus contribute to the perceived control and efficiency in the purchasing process (Ameen et al., 2021). In contrast, safe technologies and ethical aspects primarily affect the emotional dimension of the customer experience (Agbese et al., 2023). Data protection, transparency in the handling of personal data and the feeling of being respected and protected are decisive emotional elements that significantly influence the experience in smart stores. Studies show that the perceived protection of personal data in particular is a key factor influencing the acceptance of smart technologies (Budiharseno & Kim, 2023). In the field of human-computer interaction, mainly AI, researching interactive technologies in a tangible retail setting has been demonstrated to enhance comprehension of the CX and its outcomes. These outcomes are linked to constructs such as customer satisfaction, loyalty, reuse intention, customer retention, word of mouth and purchase intention (Chang et al., 2023). Statistics indicate that approximately half of the customers will not return to a store if they have had a poor experience (Kishen et al., 2021). As smart stores rely on smart technologies to shape shopping environments, they offer new and immersive touchpoints that influence the cognitive, emotional, sensorial, and social dimensions of customer experience (Vadruccio et al., 2024). Additionally, given that smart stores are a novel combination of various technologies and services, it is reasonable to assume that CX will also be redesigned (Ameen et al., 2021). Therefore, it is crucial to prioritize providing a positive CX to retain customers in the long run. Research about online retail indicates that the utilization of ethical technologies can effectively promote customer satisfaction and foster long-term customer loyalty (Tiutiu et al., 2025).

3. Research Framework

We adapted the model developed by Tiutiu & Dabija (2023), which incorporates the constructs of safe technology, ethical aspects, and customer-friendliness, as the findings of their study clearly underscore the need for empirical investigation within the context of smart, technology-driven store experiences. Figure 1 illustrates the research framework. The hypotheses along with its composition are presented below.

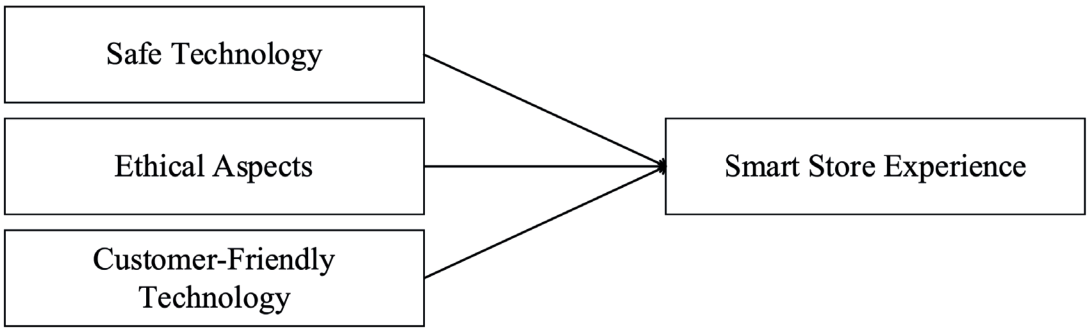

Figure 1: Conceptional research model. Source: According to Tiutiu & Dabija, 2023.

3.1 Safe Technologies in Smart Stores

Advanced smart technologies such as computer vision or customer tracking can analyze customer purchasing behavior, enabling the identification of trends and future purchasing patterns of the smart store customers (Jordan et al., 2025). This technology uses information collected during the purchase process to generate personalized purchase suggestions (Kishen et al., 2021). A major issue arising from the use of customer behavior and purchase analytics in retail is that the implementation of the technology and the resulting commercial benefits to retailers come at a potentially disproportionate cost to privacy (Gregorczuk, 2022). Therefore, apprehensions about misusing digital financial data can increase discomfort (Pillai et al., 2020). Customers may have concerns about how smart technologies are used in a smart store and whether the associated collection and management of their data is transparent and secure. Gregorczuk (2022) shows how monitoring and data collection can undermine customer privacy. Studies in China indicate that a clear and focused communication of secure digital payment methods can enhance trust in them (Qu et al., 2022). Prioritizing customer privacy is crucial given that customers are required to share their personal and financial data with the smart store's integrated technologies. This information must be treated as strictly confidential (Ameen et al., 2020). Smart stores should aim to improve CX by creating seamless, engaging experiences that address customers' concerns about the security of their personal information (Kishen et al., 2021).

Hypothesis 1: Safe technologies have a positive influence on customer experience within smart stores.

3.2 Ethical Aspects in Smart Stores

Following the consideration of safe technology, the question that arises pertains to its alignment with social norms and values. There are various definitions and fields of ethics. Essentially, ethics is the discipline concerned with distinguishing between right and wrong, and with exploring the moral obligations and duties of individuals (Siau & Wang, 2020). Ethics serve as the basis for all decision-making processes. However, there is no singular universal ethic that can be applied comprehensively; instead, principles must be tailored to specific situations (Ibiricu & Made, 2020). The growing integration of software and associated hardware with AI requires clear regulation to build and maintain trust between customers and technologies (Ibiricu & Made, 2020). In this context, the term "ethical AI" has become widely used. Based on the recommendations of high-level expert groups, the European Union has defined four key principles of ethically sound AI: Respect for Human Autonomy, Prevention of Harm, Fairness, and Explicability (Siau & Wang, 2020). Failing to comply with these ethical principles can cause severe and lasting damage to a vendor's reputation. Moreover, if technology is implemented in a way that is perceived as unlawful or unethical, it can lead to a significant loss of customer trust and to unfavourable experiences (Ibiricu & Made, 2020). Therefore, the positive potential of AI-based technologies integrated into smart stores must be carefully balanced against possible negative consequences arising from insufficient ethical consideration. To ensure fairness and transparency, the benefits of these technologies should be made accessible to all customers, rather than being limited to a select group. In this context, the customer perspective is crucial, as customers ultimately determine whether they accept and use the technology (Budiharseno & Kim, 2023). Their perceptions, concerns, and expectations directly influence the customer experience and play a decisive role in the long-term success of smart stores.

Hypothesis 2: Ethical aspects have a positive influence on customer experience within smart stores.

3.3 Customer-Friendly Technology in Smart Stores

Customers can experience an immersive and pleasurable shopping environment through advanced smart retail technology. According to Chen & Chang (2023), a customer-friendly experience with the technologies in a smart store has two main aspects: ease of interaction and usefulness of interaction. Ease of interaction represents the actual difficulty of interacting with the technologies. Usefulness of interaction describes the degree to which an interaction contributes to generating a more efficient shopping experience (Chen & Chang, 2023). Both aspects have a high influence on the purchase intention and the associated experience with the smart store (Chen & Chang, 2023). However, concerns about consumer acceptance and psychological responses to smart store technologies surface when consumers must cope with advanced technologies (Jordan et al., 2023). Additionally, Khan & Iqbal (2020) highlighted the challenge of replicating human interaction in digitized customer service, suggesting a potential limitation to the positive influence of customer-friendly technology on customer experience (Roy et al., 2018). To overcome the lacking human-to-human interaction, customers at smart stores can enjoy personalized, seamless, and enjoyable shopping experiences facilitated by advanced technology (Chen & Chang, 2023). Based on these findings, it can be assumed that by offering superior and individualized retail services, smart retail technologies have the potential to enhance the customer experience.

Hypothesis 3: Customer-friendly technology has a positive influence on customer experience within smart stores.

4. Research Methodology

4.1 Data Collection

The data collection period spanned from November 15th to December 28th, 2023. During this time, a total of n = 402 complete data sets were collected. The survey was distributed via multiple digital channels, including social media, messaging services, email and online panels in Germany, with a deliberate focus on consumers belonging to Generation Z. This customer segment is considered especially pertinent to the investigation of smart stores owing to its high level of technological affinity, its role as an early adopter of smart technologies, and its growing economic significance (Kim et al., 2022). The behavioral and perceptual patterns of this generation serve as meaningful indicators for anticipating future developments in the retail sector (Kim et al., 2022).

The survey uses a quantitative approach chosen for its advantages in terms of standardization and comparability (Backhaus et al., 2023). Data were collected using an online questionnaire in Lighthouse (Sawtooth) given that online questionnaires are efficient for collecting large amounts of data within a limited timeframe while also reaching a large and diverse number of respondents at low cost (Backhaus et al., 2023). These characteristics render online questionnaires particularly suitable for exploratory research in technology-related fields, where rapid data collection and broad accessibility are essential (Backhaus et al., 2023).

To ensure a consistent and sufficient understanding of smart stores among all participants, the questionnaire commenced with a self-produced explanatory video (see Appendix 1). This video illustrated a typical shopping journey in a smart store, showcasing relevant technologies and service interactions, such as autonomous checkout, digital signage and mobile assistance. The visual-narrative format served to reduce variability in prior knowledge, facilitated cognitive accessibility, and thus contributed to more informed and consistent responses across the sample. Subsequently, participants were asked to indicate their level of agreement with various items, using five-point Likert scales. To minimize order effects, the items were displayed in a randomized sequence. Finally, sociodemographic data were collected to enable ex-post analysis of sample heterogeneity and control for potential biases in subsequent evaluations (see Table 1).

While this broad distribution enabled efficient outreach, it also posed the risk of self-selection bias, as individuals with a greater interest in technology or digital retail concepts may have been more likely to participate. To mitigate this risk, the invitation text was designed to be neutral and accessible, targeting a general audience and not assuming any prior knowledge (Backhaus et al., 2023).

Item	Category	Frequency	%
Gender	Male	143	35.6
	Female	249	61.9
	Diverse	2	0.5
	Not specified	8	2.0
Age	Generation Z	270	67.2
	Generation Y	66	16.4
	Generation X	43	10.7
	Baby Boomers	23	5.7
Highest educational qualification	No high school degree	14	3.5
	High school degree	111	27.6
	Completed apprenticeship	68	16.9
	Bachelor, Master's degree or higher	209	52.0

Table 1: Sociodemographic data of the total sample. Source: Own research, 2023, *n* = 402.

4.2 Scales

The associated items were selected from the scales of Tiutiu & Dabija (2023) and extended by validated scales of Inman & Nikolova (2017) (see Table 4). Each item is constituted by a statement on a five-point Likert scale (1 = total disagreement and 5 = total agreement). Since the online questionnaire has been distributed primarily to German citizen, the English items have been translated into German with the back-translation method by involving independent language experts. The translation process emphasized the necessity to expand the original items with suiting examples to ensure comprehensibility.

To confirm the reliability, consistency and validity of the data, the mean, standard deviation (SD) and

Cronbach's alpha coefficient (> 0.7) were analyzed using SPSS. The Kaiser-Meyer-Olkin (KMO) criterion (> 0.7) and Bartlett's test of sphericity were also analyzed as these are specific to exploratory factor analysis (Kumar et al., 2017). The outcomes are displayed in Table 2 and confirm the reliability and validity of the measurement for all constructs except ethical aspects, which yielded slightly lower internal consistency (Cronbach's α = 0.683). However, this value is considered acceptable for new constructs in exploratory research where thresholds above 0.60 can be considered acceptable (Gliem & Gliem, 2003; Hair Jr et al., 2010). Additionally, the slightly reduced internal consistency may reflect the multidimensional and subjective nature of ethical considerations in the context of smart stores.

Construct	Items	Mean	SD	α	KMO	Bartlett	Eigen-value	% variance
Safe technology	4	3.538	0.675	0.724	0.805	< 0.001	2.132	16.402
Ethical aspects	4	2.105	0.755	0.683	0.805	< 0.001	1.135	8.735
Customer-friendly technology	5	3.992	0.641	0.794	0.805	< 0.001	3.945	30.347
Smart store experience	11	3.517	0.617	0.864	0.902	< 0.001	4.774	43.402

Table 2: Reliability, consistency and validity tests on the total sample.
Source: Own research, 2023, *n* = 402. KMO: Kaier-Meyer-Olkin; SD: standard deviation.

4.3 Data Analysis

The data analysis was conducted in two steps. First, an exploratory factor analysis (EFA) was performed to examine the dimensional structure and validity of the constructs; second, multiple regression analyses were applied to test the hypotheses and determine the influence of the independent variables on the smart store experience.

Prior to the analysis, incomplete questionnaires were removed to reduce bias and ensure data quality (Backhaus et al., 2023). The constructs safe technology, ethical aspects, customer-friendly technology, and smart store experience were then subjected to an exploratory factor analysis with varimax rotation (Williams et al., 2010). This statistical method is used to uncover latent structures among observed variables and is particularly useful in the early stages of scale development and validation (Williams et al., 2010). Principal axis factoring was selected as the extraction method to identify the common variance among the items. The extracted factors are interpreted as latent variables, which serve as the conceptual basis for the subsequent regression analyses. Table 4 shows the factor loadings, eigenvalues and explained variance for each construct. Only factors with eigenvalues greater than 1 were retained (Backhaus et al., 2023). During the analysis, two items from the customer-friendly technology construct were excluded due to low factor loadings. A semantic review revealed that these items referred to back-end processes that are not directly perceivable by customers. Their removal increased internal consistency and improved the overall model fit.

Based on the factor structure identified in the first step, multiple regression analyses were conducted to examine the influence of three independent variables – safe technology, ethical aspects and customer-friendly technology – on the smart store experience. Prior to conducting the multiple regression analyses, the dataset was tested for the linear relationship between the variables, outliers, the independence of the residuals, multicollinearity, homoscedasticity and the normal residual distribution (Hair Jr et al., 2010; Huber et al., 2007; Velleman & Welsch, 1981). The data showed a good fit for all conditions; therefore, the prerequisites for multiple regression were met. Each regression model was then evaluated in terms of its fit, statistical significance and the strength of the individual predictors.

5. Findings

The results of the exploratory factor analysis revealed a two-factor structure for the smart store experience construct. Therefore, the original construct was divided into two sub-dimensions: store-based interaction and product-based interaction. A semantic analysis confirmed that the first factor encompasses items related to the overall shopping experience and interaction with the smart store, while the second factor includes items focused on the interaction with and evaluation of individual products (see Table 4). Based on these findings, we re-evaluated the reliability, consistency, and validity of the two new constructs (see Table 4). The analysis indicates satisfactory reliability and validity, supporting the suitability of the revised two-dimensional structure for further analysis.

Construct	Items	Mean	SD	α	KMO	Bartlett	Eigen-value	% variance
Store-based interaction	6	3.682	0.698	0.849	0.891	< 0.001	4.341	48.233
Product-based interaction	3	3.321	0.807	0.782	0.891	< 0.001	1.218	13.536

Table 3: Reliability, consistency, validity and descriptive parameters on selected constructs.
Source: Own research, 2023, *n* = 402. KMO: Kaier-Meyer-Olkin; SD: standard deviation.

5.1 Exploratory Factor Analysis

The smart store experience treated as a holistic construct reveals that all item factor loadings exceed 0.4 (see Table 4). According to Hair Jr et al. (2010), loadings above 0.3 are considered significant for sample sizes larger than N = 350. With a sample size of n = 402 participants, the observed values are therefore deemed acceptable. Nonetheless, based on the findings from the exploratory factor analysis, the two sub-dimensions were retained for further analysis. Their results were examined individually, compared with one another, and subsequently evaluated in relation to the smart store experience.

Items	Item loading	Reference
Safe technology		
The implementation of new technology is safe despite the considered risk regarding transactions.	0.592	Tiutiu & Dabija, 2023
The use of new technology is safe when it comes to the protection of privacy.	0.586	
Thanks to new technologies such as AI, the shopping experience can be improved.	0.613	
It is of high importance that a certain technology is perceived as pleasant and therefore accepted.	0.524	

Ethical aspects		
It is justifiable that certain technologies do not help customers who are not expected to buy.	0.424	Tiutiu & Dabija, 2023
Is it ethically justifiable to automatically recommend a more expensive product when a cheaper product might be more suitable for the customer.	0.718	
Is it justifiable to prefer certain customers – that only certain customers are eligible to use technologies, for example: Customer classifications in apps which could lead to different discounts.	0.569	
Is it ethically justifiable to put pressure on customers so that they buy as much as possible.	0.699	
Customer-friendly technology		
I believe the use of this specific technology will be clear and easy to understand.	0.576	Inman & Nikolova, 2017
It will be easy for me to use this technology.	0.716	
It would be easy for me to use this technology in the store.	0.770	
This technology helps to provide fast, personalized and qualitative services.	0.403	Tiutiu & Dabija, 2023
This technology includes the transaction process, so everything works out well.	0.577	
Store-based interaction		
I can easily interact with the smart store.	0.532	Tiutiu & Dabija, 2023
The shopping experience seems safe.	0.543	
This technology enables me to enjoy new experiences.	0.585	
I believe it would be useful to use this technology in the store.	0.733	Inman & Nikolova, 2017
I believe this technology will influence my shopping experience positively.	0.778	
I believe this technology will add value to the overall service of the store.	0.754	
Product-based interaction		
It helps me to make better decisions regarding products I might want to buy.	0.654	Tiutiu & Dabija, 2023
It helps me to find the right products.	0.697	
It helps me to evaluate the product.	0.739	

Table 4: Factor loading exploratory factor analysis. Source: Own research, 2023, $n = 402$.

During the analysis, the construct store-based interaction was reduced by one item due to a low factor loading (0.351) leading to an improvement in Cronbach's alpha after its removal. The same procedure was applied to one item in the product-based interaction construct. The results of the exploratory factor analysis can be visualized in the Figure 2.

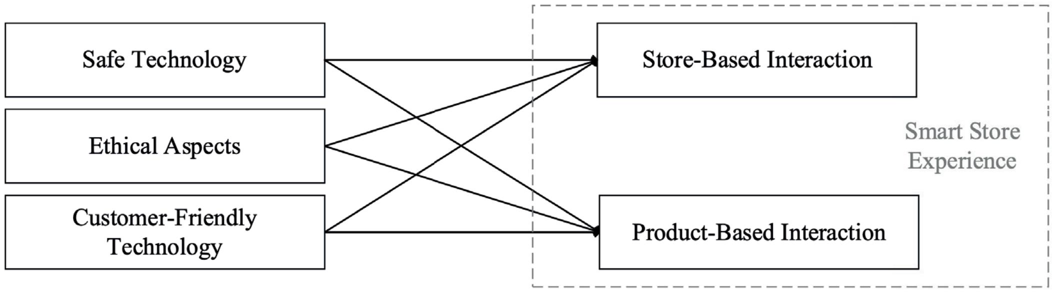

Figure 2: Adjusted conceptual model with two sub-dimensions.

5.2 Sub-Dimensional Multiple Regression Analysis

Multiple regression analyses were conducted using safe technology, ethical aspects and customer-friendly technology as the independent variables. Following the factor structure of the exploratory factor analysis, the dependent variable in the first model was the sub-dimension of store-based interaction. The same analysis was subsequently performed with product-based interaction as the dependent variable (see Table 5). Figure 3 shows the results obtained from these models.

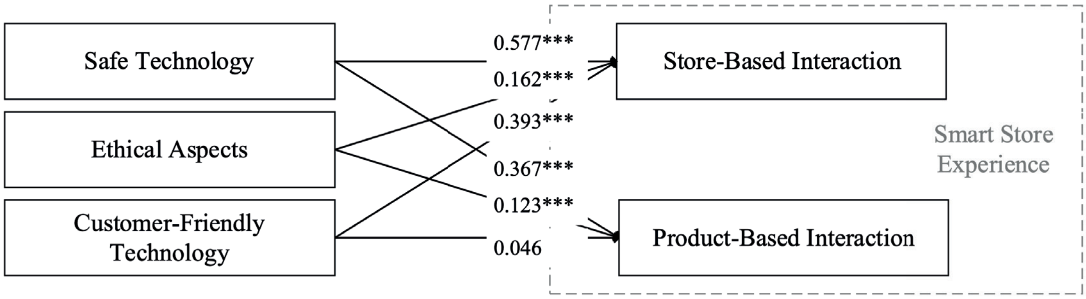

Figure 3: Adjusted conceptual model with two sub-dimensions and regression coefficients.
Source: Own research, 2023, *n* = 402; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For store-based interaction, the model shows a high goodness of fit, with a coefficient of multiple determination of $R^2 = 0.626$ (adjusted $R^2 = 0.623$) and is statistically significant ($p < 0.001$). All three predictors demonstrate significant and positive effects. Safe technology emerges as the strongest predictor ($\beta = 0.577$, $p < 0.001$), indicating that perceptions of technological safety play a central role in shaping customer experience within smart stores. Customer-friendly technology also exerts a considerable influence ($\beta = 0.393$, $p < 0.001$), suggesting that intuitive and user-friendly features contribute meaningfully to a positive shopping experience. Although the effect is smaller, ethical aspects still have a statistically significant impact ($\beta = 0.162$, $p < 0.001$), underscoring the importance of fairness and transparency in how customers perceive and engage with the store.

In contrast, the product-based interaction model shows a lower fit, with an R^2 of 0.149 (adjusted $R^2 = 0.142$). Nonetheless, the model is statistically significant ($p < 0.001$). The pattern of effects differs from the store-based interaction model. Safe technology again shows a significant influence ($\beta = 0.359$, $p < 0.001$), although the effect is weaker. Ethical aspects also have a significant, albeit smaller, effect ($\beta = 0.115$, $p = 0.008$), indicating that fairness matters even in more task-based interactions. In contrast, customer-friendly technology does not exert a significant effect in this context ($\beta = 0.025$, $p = 0.359$).

The confidence interval for this variable cross zero ([-0.049, 0.135]), suggesting that usability-related features have little to no influence on how customers interact with individual products in smart stores. Overall, these findings highlight safe technology as the most robust and consistent predictor across both interaction levels. While ethical aspects also play a relevant role, particularly in establishing trust, customer-friendly technology appears to be more influential at the overall store level than in product-specific interactions. This is consistent with the exploratory factor analysis results, in which product-based interaction was associated with a comparatively low eigenvalue.

Model	Variable	Beta	Standard error	T-Value	Sig.	95% Confidence Interval
Store-based interaction	Safe technology	0.577	0.025	18.304	< 0.001	[0.408, 0.506]
	Customer-friendly technology	0.393	0.023	12.500	< 0.001	[0.244, 0.335]
	Ethical aspects	0.162	0.023	5.288	< 0.001	[0.076, 0.165]
Product-based interaction	Safe technology	0.367	0.050	7.281	< 0.001	[0.268, 0.466]
	Customer-friendly technology	0.043	0.047	0.918	0.359	[-0.049, 0.135]
	Ethical aspects	0.123	0.046	2.677	0.008	[0.033, 0.213]

Table 5: Sub-dimensional multiple regressions. Source: Own research, 2023, *n* = 402. Sig.: significance.

5.3 Aggregated Multiple Regression Analysis

To address the hypotheses as a whole, multiple regression was performed with the construct smart store experience treated as a holistic concept (see Figure 4). The overall model of the smart store experience shows a high goodness of fit, with a multiple coefficient of determination of $R^2 = 0.570$ (adjusted $R^2 = 0.567$). The model of smart store experience is statistically significant ($p < 0.001$).

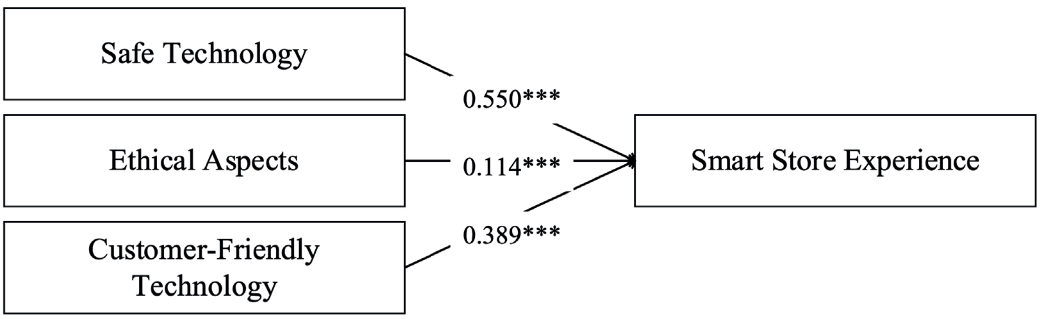

Figure 4: Aggregated multiple regression. Source: Own research, 2023, *n* = 402; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Again, safe technology emerges as the strongest predictor ($\beta = 0.550$, $p < 0.001$), indicating that perceived safety in the use of smart technologies plays a key role in shaping the overall customer experience in smart stores, therefore H1 can be accepted (see Table 6). Customer-friendly technology also shows a substantial and highly significant influence (β = 0.389, p < 0.001), suggesting that intuitive, easy-to-use systems meaningfully contribute to a positive experience, thus accepting H2. Although smaller in effect size, ethical aspects remain a significant factor (β = 0.114, p < 0.001), accepting H3 and highlighting the importance of fairness, and transparency.

Model	Variable	Beta	Standard error	T-Value	Sig.	95% Confidence Interval
Smart Store Experience	Safe technology	0.550	0.038	16.290	< 0.001	[0.543, 0.692]
	Customer-friendly technology	0.389	0.035	11.543	< 0.001	[0.337, 0.475]
	Ethical aspects	0.114	0.035	3.477	< 0.001	[0.052, 0.188]

Table 6: Aggregated multiple regression. Source: Own research, 2023, *n* = 402. Sig.: significance.

6. Discussion and Implications

Considering the increasing implementation of smart technologies in physical retail environments, this study contributes to a deeper understanding of how ethical aspects, and safe and customer-friendly technology influence the CX in smart stores. The findings confirm the significance of all three examined constructs in shaping a positive customer experience (Chang et al., 2023; Chang & Chen, 2021; Netscher et al., 2025; Tiutiu et al., 2025) and reveal important differentiations between store-based and product-based interactions. The distinction between store-based and product-based interactions is grounded in both the results of the exploratory factor analysis and the semantic analysis of the item content. While the factor analysis revealed a two-dimensional structure within the smart store experience, the subsequent interpretation of item meaning confirmed that one dimension captures interactions with the overall store, whereas the other reflects interactions at the product level. This empirically derived distinction provides a differentiated understanding of how smart technologies shape customer experience in smart stores. Safe technology, ethical aspects and customer-friendly technology had a significantly strong influence on the customer experience of store-based interactions. This suggests that customers primarily evaluate smart stores based on how seamless, safe and convenient the environment is perceived to be (Chang & Chen, 2021). In contrast, safe technology and ethical aspects had a weaker, yet still measurable effect on product-based interactions. Surprisingly, however, customer-friendly technology had no effect on the experience of product-based interactions. This may be due to a lower familiarity with such technologies or their limited presence in current smart stores (Park & Zhang, 2022). While store-based technologies in smart stores are already perceived as standard and indispensable, product-based technologies appear to be less pertinent in the current shopping experience and require further development and customer engagement (Grewal et al., 2023). These findings emphasise the importance of retailers first ensuring a smooth and trustworthy in-store environment before focusing on improving product-level interactions.

6.1 Theoretical Implications

This study makes three significant contributions to the theoretical understanding of CX in smart stores. Firstly, it extends existing technology acceptance models, such as the TAM and the UTAUT, by incorporating the concepts of safe technology, ethical aspects, and customer-friendly technology into the analysis of CX in smart stores. Moreover, the study adapts Tiutiu & Dabija's (2023) model for a physical retail context, which has thus far remained unexplored. While these studies are often applied to online retail settings, this study demonstrates their applicability and relevance in smart stores, thereby expanding the scope of CX research in retail. Secondly, the findings refine the understanding of the dimensionality of CX in smart retail settings. Identifying store- and product-based interactions as distinct sub-dimensions of CX provides a more nuanced view of how customers perceive and evaluate smart stores. This distinction in dimensions aligns with Lemon and Verhoef's (2016) CX framework, further specifying the effect of different types of technological interaction, ranging from holistic, system-level experiences to concrete, product-level support, on customer experiences. Separating these two dimensions suggests that CX in smart stores is structured along multiple interaction layers, each shaped by different technological attributes. Thirdly, this research enhances the understanding of the technology readiness of previous studies by showing that customer experience in smart stores increases when they are perceived as safe and ethical regarding data privacy (e.g. Park, 2020).

6.2 Practical Implications

The findings indicate that retailers do not only have to enhance the quality of in-store interactions but also recognize the importance of fostering seamless customer engagement with products as a distinct objective. In terms of store-based interaction, the objective is to create a physical store that is enhanced by smart technologies which contribute to the store's safety and service. Product-based interaction focuses on product experience, product advice and decision support. To illustrate this, technologies such as interactive digital shelf displays, mobile self-scanning devices, and AI-powered recommendations are examples of solutions that enable engaging and personalized product experiences (Vadruccio et al., 2024). To ensure that the customer has the best possible experience it is essential that both aspects are considered separately in the future.

A more detailed analysis of the topic allows for the identification of differences in the importance attributed to the various constructs. The interest of consumers in customer-friendly technologies is contingent upon their capacity to directly influence the customer experience in a smart store. Consequently, when implementing or improving a smart store, retailers should prioritize customer-facing technologies that visibly and directly enhance the customer experience as back-end technologies are not subject to customer judgement. Examples of such customer-facing technologies include smart mirrors in fashion retail, digital price tags, and real-time queue management systems that improve perceived service efficiency. Furthermore, there is a distinction between customer-friendly technology in product-centric and store-centric interactions. Implementing smart store technologies that prioritize usability, utility, functionality and personalized experiences will significantly improve the in-store experience. For instance, the integration of automated checkout systems (e.g., Amazon Go), or personalized shopping apps that guide customers through the store based on preferences or previous purchases, are concrete implementations that align with these expectations (Jordan et al. 2025). To optimize the customer experience, retailers should refine technologies that have a direct impact on the in-store environment. Customer convenience considerations for product-based interactions can take a back seat to the broader context of smart store implementation strategies. In the context of customer experience in smart stores, the primary focus is on secure technologies, underscoring the necessity for retailers to adhere to security protocols while providing personalized experiences through smart store technologies. It is recommended that future retail strategies should aim to ensure the privacy and confidentiality of personal data. While consumers recognize the importance of secure technologies in the context of smart stores, they do not currently associate inherent risks with existing smart store technologies. Therefore, efforts to explicitly communicate the security measures of these technologies do not need to be intensified. This highlights that the perceived value of these technologies outweighs concerns about their use and privacy, emphasizing the importance of implementing secure technologies while balancing consumer expectations and communication efforts. In both product and business-based interactions, consumers are aware of certain injustices resulting from the use of technologies in the smart store. On average, consumers do not agree that the use of technologies which discriminate between customers or work to a customer's financial disadvantage is justified. Therefore, it cannot be said that customers simply dismiss ethical concerns and have a better customer experience as a result. Rather, it is necessary to consider ethical concerns when implementing smart stores rather than assuming their absence.

7. Limitations and Future Research

This study provided valuable insights into the customer experience in smart stores. Several limitations should be acknowledged, each of which opens avenues for future research. Firstly, the findings are based on a random sample of participants from Germany, which restricts how widely the results can be generalized to other cultural and regional contexts. Future studies should replicate the research in diverse geographic regions to examine potential cultural differences in perceptions of safe technologies, ethical aspects, and customer-friendly technology. Secondly, participants engaged with the concept of a smart store via a video simulation rather than through physical interaction. While this approach ensured consistency, it may not fully capture real-world behavior and perceptions. Further research should be conducted in real or simulated smart store environments, allowing participants to interact directly with the technologies and generate more authentic responses. Thirdly, the study focused primarily on Generation Z, with older cohorts such as the Baby Boomers being less presented. As experience with smart stores may vary by age, future studies should compare generational differences in the evaluation of smart stores, particularly about ethical aspects and safety perceptions. Fourthly, the findings suggest that product-based interaction is less well explained by the applied constructs than store-based interaction. This suggests a need for further exploration into the specific drivers of product-based experiences. Future research should treat product-based interaction as a distinct and specialized field, developing constructs that reflect its unique characteristics and complexity. In summary, these limitations highlight the importance of situationally grounded and customer-centered approaches in future research. While this study is an important step in operationalizing the concept of the smart store experience, it also establishes a basis for further refinement and theoretical development in this emerging field.

8. Conclusion

The study demonstrates that safe technology, ethical aspects and customer-friendly technology have a significant influence on the customer experience in smart stores. By adapting and extending existing models to the context of smart stores, the study addresses a notable gap in the literature and contributes to a deeper understanding of CX in smart stores. The empirical findings emphasize that safe technologies have the strongest influence, followed by ethical aspects and customer-friendliness, particularly regarding store-based interactions. Differentiating between store- and product-based experiences reveals that customers evaluate smart stores on multiple levels. These insights are relevant not only for advancing academic discourse, but also for designing inclusive, trustworthy and customer-oriented smart stores.

Conflicts of Interest Statement

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix

Appendix

Appendix 1: Online questionnaire

Video introduction with self-produced video

Five-point Likert scaled items for each construct	**Fully disagree**	**Disagree**	**Neutral**	**Agree**	**Fully sagree**
Safe technology					
The implementation of new technology is safe despite the considered risk regarding transactions. The use of new technology is safe when it comes to the protection of privacy. Thanks to new technologies such as AI, the shopping experience can be improved. It is of high importance that a certain technology is perceived as pleasant and therefore accepted.					
Ethical aspects					
It is justifiable that certain technologies do not help customers who are not expected to buy. Is it ethically justifiable to automatically recommend a more expensive product when a cheaper product might be more suitable for the customer. Is it justifiable to prefer certain customers - that only certain customers are eligible to use technologies, for example: Customer classifications in apps which could lead to different discounts. Is it ethically justifiable to put pressure on customers so that they buy as much as possible.					
Customer-friendly technology					
I believe the use of this specific technology will be clear and easy to understand. Technology is useful to ensure that products are in-stock. I believe that my interaction with this technology will be clear and understandable.					

Technology is useful to provide data extraction solutions for the suppliers.					
Technology is useful for the customer data extraction solutions for the suppliers.					
It will be easy for me to use this technology.					
It would be easy for me to use this technology in the store.					
This technology helps to provide fast, personalized and qualitative services.					
This technology includes the transaction process so everything works out well.					
Smart store experience					
I can easily interact with the smart store.					
The smart store creates an experience similar to that of a real store.					
The smart store offers me the opportunity to interact with the products.					
The shopping experience seems safe.					
This technology enables me to enjoy new experiences.					
I believe it would be useful to use this technology in the store.					
I believe this technology will influence my shopping experience positively.					
I believe this technology will add value to the overall service of the store.					
It helps me to make better decisions regarding products I might want to buy.					
It allows me to enjoy being immersed in a new existing experience.					
It helps me to find the right products.					
It helps me to evaluate the product.					
Socio-demographic questions					
What is your country of residency?	*Dropdown menu featuring all possible countries*				
What is your current residential situation?	*Single choice question featuring “Rural (<5,000 inhabitants), small city (5,000–20,000), medium-sized city (20,000–500,000) and large city (>500.000)*				
What is your mother tongue?	*Multiple choice with selected languages (German, English, Turkish, Arabic, Spanish, French, Italian and a custom field to put further text answers)*				
How old are you?	*Numeric question design to type respondent's age*				
Please select your highest level of education.	*Single choice question with several answers (Secondary school, A levels, apprenticeship, bachelor's degree, master's degree or higher)*				

Source: Own research, 2023, n = 402.

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