

Disruptive Technologies: How to influence price sensitivity triggering consumers' behavioural beliefs

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ABSTRACT

The adoption of new technologies generates an attractive offer of innovative products that flood the markets. Are these products perceived as expensive or cheap? What determines the price range accepted by consumers? This research identifies behavioural variables that can modify the price perception of new technological products, that is, increase or decrease critical price thresholds. As direct value-based pricing method, Van Westendorp's price sensitivity meter is receiving increasing attention to identify acceptable prices for new technologies. We rely on arguments from the theory of planned behaviour to explore what changes consumers' critical price thresholds.

Considering a set of disruptive technologies (augmented reality smart glasses, 3D printers, writing robots, self-driving cars, hoverboard robots), a structural approach is used to explore consumers' perceived threshold prices. The main results suggest that social pressure and perceived control increase the perceived minimum price, and price sensitivity can be decreased evoking perceived ease of use.

Keywords: Disruptive technology, Van Westendorp Price Sensitivity, Planned behaviour, Augmented Reality, 3D printer, Self-driving car, Robots

1. Introduction

The investment in value creation through innovative (service) technologies and automation has found broad interest, especially among tech giants, spending more than \$500 million per year, while other firms expect valuable learnings but fear that the investment won't pay off (Wolpert & Roth, 2020; Zonni, 2019). At the same time, disruptive technologies can trigger changes in consumer behaviour and force consumers to revise their perspective on the market value of products (Melnik et al., 2019). Given the competitive environment, there is an increasing interest to identify value drivers, beyond core product attributes, that convey value for consumers and factors that influence price sensitivity in the context of adoption of new technologies (Christen et al., 2022; Natarajan et al., 2017).

Understanding and anticipating people's response to new technologies is a key aspect in designing customer-centric business and marketing strategies. This is especially relevant given the increasing importance of non-tangible value of products or services, and the observed violation of rational choice principles in pricing decisions, which needs to broaden the understanding of psychological aspects in pricing (Hinterhuber, 2015). Pricing, a strategic approach to price setting at the intersection of Marketing and Economics (Eslava, 2015), addresses this challenge as follows: In marketing and revenues management the focus is increasingly on value-based pricing methods (Steinbrenner & Turcinkova, 2021), which allow consumers' perceived price limits to be identified and purchase incentives to be generated through appropriate price setting. Likewise, conceptualizations and explorative studies allow factors to be identified that drive consumers' willingness to pay or price perceptions (Chee et al., 2020; Mercedes-Sánchez et al., 2018; López Mósquera et al., 2016), which can be exploited for an effective price communication strategy. From an economic perspective, the theory of motivated beliefs (Bénabou & Tirole, 2016) integrates in the framework of economic rational consumer behaviour elements of social psychology, which finds increasing applications.

This raises the question how motivational beliefs, with respect to the consequences of their behaviour when deciding to purchase a new technology, may trigger changes in consumers' perceived price limits and hence the acceptable price range? Our objective is to measure price sensitivity of disruptive technologies and explore what drives the range of acceptable prices, which allows to develop appropriate communication strategies to capture the generated value.

Concretely, we set up the following three research questions: (1) What is the acceptable price range and the relative price sensitivity of consumers for a considered technology? (2) What determines consumers' price thresholds for new technologies? (3) How can we leverage the identified drivers to decrease consumers' price sensitivity?

To address these questions, we consider jointly measurements of perceived price thresholds as established by value-based pricing methods and the fundamentals from technology adoption theories.

The measurement of value perception, is based on the the principal insights from behavioural pricing, which suggest that consumers evaluate products or services based on a reference price and that consumers have an upper and lower limit of acceptable prices (Adam, 1969; Stoetzel, 1969). Srivastava et al. (2022) review several theories that provide explanations for reference prices in the consumers' decision process, which is in general based on prices from previous purchases that the consumer keeps in mind as reference for comparison. This holds also for value-based pricing on digital platforms, where the seller history has been identified as a value-based pricing factor (Christen et al., 2022). However, for new products, such as disruptive technologies, which have not yet consolidated, reference pricing is imprecise or not applicable since there are no historical prices or experience to rely on. In these cases, without purchase history, direct survey-based methods allow the willingness to pay (WTP) of consumers to be identified or to establish reasonable psychological price ranges (Lipovetsky et al., 2011). For determining acceptable prices for new technologies, the Van Westendorp price sensitivity meter (vW-PSM; Van Westendorp, 1976) in particular has recently found broad applications. Examples are the identification of acceptable price ranges for new technologies, such as 4G service (Khandker & Joshi, 2018), mobility as a service (Stopka et al., 2018), electric cars (Larson, 2014) or the service sector (Dominique-Ferreira et al., 2019; Ceylana et al., 2014).

In order to explore what drives consumers' perceived price thresholds or price sensitivity of new technological products, we draw on the knowledge from technology adoption theories. Across the wide range of exploratory technology adoption models (see for instance Venkatesh et al., 2003), the theory of planned behaviour (TPB) is one of the baseline models which has been used to explain consumers' willingness to pay (Sánchez et al., 2018), which is understood as a variable of behavioural intention that captures the generated value. Other studies have explored the effect on price sensitivity (PS), however,

considering the role of PS as latent variable in the framework of technology adoption the results are ambiguous (Bhutto et al., 2022; Brandão & Gonçalves da Costa, 2021; Hsu et al., 2017) and don't allow to draw inferences on concrete pricing strategies.

For strategic customer-centric pricing decisions we need to understand which elements influence the personal range of price acceptability of consumers (Dominque-Ferreira et al., 2020). To address this multidimensional problem, the authors make use of the vW-PSM, as psychological pricing model, using segmentation by star ratings (as a quality signal), which is identified as an influential factor of the acceptable prices. Furthermore, Talebian and Mishra (2018) find that peer-to-peer communication about new technology effects consumers' willingness to pay as consequence of the perception of the technology.

In this paper, we study how consumers' range of price acceptability can be amplified, reduced or shifted by motivational beliefs, with the underlying argumentation based on technology adoption theories. Concretely, an exploratory approach is used to consider jointly well established psychological values that influence the consumers' adoption of new technologies, which potentially intervene in consumers' value perception, and the acceptable price range. This allows to derive actionable insights for price setting and communication through the influence of the limits of acceptable price intervals and hence the price sensitivity for disruptive technologies. Hence, we aim to contribute to bridge the gap between value-based pricing practice and exploratory insights what drives consumers' intended behaviour and beliefs. That is, the focus of the research is to identify which variables influence perceived price thresholds of new technologies.

Concretely, for a selection of disruptive technologies, first we use the vW-PSM model to identify the acceptable price range. Subsequently, we consider potential drivers of the estimated price thresholds, which were identified from a literature review on the evolution of the technology adoption theories and the relation to value assessment. The theory of planned behaviour (TPB), which has once again come to prominence in the context of disruptive technologies (Ajzen, 2020), builds the fundamental theory for the analysis, with the (motivational) constructs being aligned with subsequent technology adoption theories and economic reasoning. Analyzing the effects of the identified elements on perceived price thresholds allows comparative statics with respect to the acceptable price range to be derived and provides firms with tools to impact consumers' price sensitivity through an appropriate communication strategy.

The analysis is applied to a set of disruptive technologies (augmented reality smart glasses, 3D printers, self-driving car technology, hoverboard robots, scribit robots), which have been selected based on their level of maturity according to the Gartner Hype Cycle (Herdina, 2020; Gartner, 2020; Ray, 2020; Goehrke, 2019). We use survey data from a laboratory experiment, where students experimented with the analyzed technologies and subsequently answered a 20-minute questionnaire, with a total of 253 complete responses. The model is estimated using partial least square structural equation model, which allows to address the exploratory and predictive nature of the approach.

The main results suggest that an increase in the importance of social opinion significantly increases the perceived minimum price of almost all considered technologies. Furthermore, for AR Smart Glasses, Scribit Robot, Segway Robot and Self-driven car, managers can increase the perceived minimum price as well as the perceived maximum price by creating stimuli evoking the need for closure. Finally, for AR Smart Glasses and Robotic technologies, evoking through the value communication the perceived ease of use of these technologies reduces consumers' price sensitivity.

The unique contribution of this paper to the pricing of disruptive technologies is the explanation of how consumers' perceived critical price thresholds for the purchase of new technologies can be affected by motivational beliefs and personal traits. Since reference price theories are in general not applicable to explain value assessment of new technologies, we propose to make use of the theoretical arguments from technology adoption theories, concretely from the theory of planned behaviour, as the natural context of the assessment of new technologies. These theories, focused on explaining the intention to adopt a particular technology, are a necessary requirement for a succesful market implementation, however, this is not enough to generate economic returns. The inherent value assessment by consumers (which drives the desired behaviour) needs to be captured in the price and reinforced through value communication. Hence, we claim that well identified variables of technology adoption (which have been conceptually related to value or price sensitivity) may also trigger consumers' perceived price limits for these products. That is, the joint consideration of the theory of planned behaviour and a direct pricing approach for new products allows to identify what allows raising of prices and what does not.

From a management perspective, if the price exceeded the perceived quality or was too low the organization would lose customers. Hence testing consumers' value assessment through perceived price thresholds before going to the market is crucial to be successful. Our study contributes to the understanding how consumers' beliefs influences their price perception and PS; which enables managers, through an effective communication strategy, to favourably influence the perceptions of value and price sensitivity without actually changing the price, or to concentrate the investment on particular elements that improve the desired perception (Dominique-Ferreira et al., 2020; Hinterhuber, 2015; Bar-Isaak et al., 2010, 2012).

2. Conceptual framework & hypothesis development

The disruptive nature and increasing importance of technological product innovations for business growth, can be considered from different perspectives, which lies at the intersection of Marketing and Economics.

For instance, in retail and marketing, disruptive technologies – ranging from augmented reality and virtual reality to robots and intelligent automation based on natural language processing or artificial intelligence, among others – allow the creation or enhancement of value for customers or new experiences to be offered and at the same time the generation of a competitive advantage through operational excellence (Kotler et al., 2021; Wolpert & Roth, 2020).

From an economic point of view, disruptive technologies are considered prerequisites of the transition to new ways of consumption and production, opening up new business cycles and changing the generation of benefits and pricing (Melnik et al., 2019).

In this paper, we study how consumers' behaviour beliefs, as prerequisites of purchase, affect their price sensitivity for the following disruptive technologies: augmented reality smart glasses, 3D printers, self-driving car technology and robotics such as scribit robots or segway robots, which are briefly introduced in the following, highlighting the need for the assessment of acceptable prices and PS.

For the selection of the four technologies on which the study is based, we relied on their high level of maturity and widespread adoption in the market according to the model developed by Gartner in its Hype Cycle. The Gartner Hype Cycle is a graphical representation in the form of a curve that depicts the maturity and adoption of technologies and apps and how they are potentially relevant to solving real business

problems and seizing new opportunities (Gartner, 2022). This model is commonly accepted by the scientific community to perform analysis, detection and monitoring of emerging technologies (Chen & Han, 2019; Dedehayir & Steinert, 2016; Kaivo-oja & Lauraeus, 2018; Barlex, 2017). In 2020, AR is no longer considered an emerging technology and is moved to pilot to productivity in the enterprise space (Herdina, 2020). Also, Autonomous Driving Level 3 and Robotics are in climbing slope in 2020 (Gartner, 2020; Ray, 2020), and 3D Printing reached maturity in 2019 (Goehrke, 2019). We therefore find AR, 3D Printers, Self Driving Car and Robotics technologies in the “productivity plateau” position of the Hype Cycle in the years 2019 and 2020, highlighting their maturity and readiness to generate market returns.

Augmented reality (AR) as front-end technology in marketing (through AR smart glasses, AR apps, AR magic mirrors, Avatars etc.) provides an opportunity for the customer to be immersed in different realities, allows for a high degree of personalization, and at the same time, the touchless interactions between customers and firm (which has become especially interesting since Covid-19, overcoming physical distances) is considered to provide a different way of living, beyond the technical solution (Papagiannis, 2020, Song et al., 2020). Porter and Heppelmann (2018) were among the first academics to emphasize the need to leverage this technology within the firm strategy, and Dalton and Gillham (2019) predict a significant boost of the technology-driven gross domestic product through AR or VR solutions; which since the hype about the metaverse (Hall & Li, 2021) is expected to be even stronger. In this context, Erdmann et al. (2021) analyze consumers’ perceived value of AR smart glasses and find that the value is determined through experiential, technical and social dimensions rather than an economic cost-benefit analysis. In the same line, Pillai et al. (2020) state that the intention or adoption of AI-based technology is context-specific. What the majority of existing studies on the effect of AR technology have in common is the focus on consumer experience and social expectations that drive the intention to adopt new technologies (McLean & Wilson, 2019; Dacko, 2017; Kalantari & Rauschnabel, 2016). However, the purely exploratory focus by the cited papers doesn’t allow the assessment of concrete values or price magnitudes, which is considered necessary for a planned pricing strategy and profitability analysis of investment in the technology.

3D printers, as an innovative technology, have experienced a high annual growth rate and potential for penetration of many industries such as medicine, education, construction, engineering, designers etc. (Petrick & Simpson, 2015). Likewise, the 3D

technology is developing in other areas, for example in manufacturing smaller and faster components like different sensors and other electronic devices (Xu et al., 2017). Given the decrease in costs (Moilanen et al., 2015), and increased speed of printing (Cohen et al., 2014), big retail companies like Amazon and Tchibo joined the game to invest in this technology within their product line. The demand of basic CAD skills for the users implies a sort of barrier, however, the increasingly user-friendly interfaces, software, and open resources available in the market have made the technology available to a broad consumer segment (Holzmann, 2018), which emphasizes the need of assessment or reconsideration of the market value and consumers' price sensitivity when considering the purchase of 3D printers.

Self-driving car technology has been a hot topic in recent years. The Society of Automotive Engineers (SAE international, 2016) divides this technology into six levels to define the state of automation from level zero to level five. Level zero means the car is without any automation option and the driver needs to be 100% involved in the driving process. At level three, humans need to drive but there is driving assistance available under limited conditions. From level four onwards, people will no longer be required to drive. And level six means that the system can take over driving under all conditions. Although self-driving solutions are supposed to help in optimizing the road traffic and reduce crashes due to human error (Cohen et al., 2018), as a very recent technology, it still faces resistance to be accepted in the market (Baccarella et al., 2020), such as ethical issues (Lin, 2015), security and safety worries (Liu, 2018), and uncertainty as regards political decisions (Marchau, 2018). This is in line with Chee et al. (2020), who show that the cognitive response such as the perceptions towards service quality attributes is significant in the formation of consumers' WTP for automated vehicles. Respective the perceived value of the technology, Elvik (2020) estimates that consumers are willing to pay an extra \$1000 to \$7000 for this innovative technology. Currently the new self-driving car is considered too expensive for most of the respondents of the cited study, however, according to the authors, the price is expected to be lower in future. Some researchers have found evidence that the willingness to pay for self-driving cars, analogous to other products, depends on age, gender and purchasing power (Abraham, 2017; Bansal, 2017; Liu, 2018) or on social opinions (Talebian & Mishra, 2018). However, the acceptable price range or PS of this technology has not yet been analyzed.

Robotics are transforming consumer-firm interactions in terms of the distribution of certain tasks and labour (Granulo et al., 2018), and find broad applications in different

areas such as services, manufacturing and even in medical treatments (Lai, 2018). There exists a wide range of service robots with distinct functions and technologies: service robots for hotels and restaurants, reception robots, scribit robots, segway robots, etc. The academic literature on these types of robots is sparse. The Segway robot was created in 2001 by Dean Kamen, and, according to Pinto (2012), this two-wheeled robot is needed for intelligent transportation systems, providing flexible carrying capacities as a modern technology. However, obstacles to adoption are: particular requirements of environmental conditions; high cost; their heavy weight; the need for better obstacle avoidance technology (Ye, 2004); and stability (Prabhakar, 2020). Further concerns consider the safety of the equipment (Park, 2018), and the need for new legislation to avoid accidents and protect consumer rights (Forsch, 2017). The price range of different robots is exceptionally large depending on function and technology, however, certain elements like RGBD cameras, sensors and other modules continue to decrease, such that the price is predicted to become affordable for the mass market (Fitzgerald & Quasney, 2017). Hence, an assessment is necessary of acceptable prices, depending on consumers' expectations. New technological solutions in general (including the introduced selection of disruptive technologies) require customer-centric marketing and value assessment (Stoppel & Roth, 2016; Rifkin, 2015). In this context, an important concept is the perceived value, which is an implicit criteria of overall value assessment used by consumers in the decision process, which has been considered by different theories as unidimensional concept of trade-offs and net benefits (Zeithaml, 1988; Dodds et al., 1991) or as multidimensional concept differentiating in utilitarian and hedonic value, emotional and rational values, etc. (for an overview see Sánchez-Fernández & Iniesta-Bonillo, 2007). The value assessment is understood as an antecedent in the adoption of technologies (Seol et al., 2016), and has through the price setting a direct effect on the firms revenues. But how to measure the value perception by consumers?

Value-based pricing (VBP) is complex due to the difficulty in evaluating value, communicating it, segmenting the market and identifying reliable measurement tools (Hinterhuber & Bertini, 2011; Hinterhuber, 2008). Moreover, scholars have found differences across industries with the technology industry showing the fewest obstacles (Steinbrenner & Turcinkova, 2021), which is reflected in increasing academic interest in value-based pricing methodologies for innovative technology solutions. Concretely, the vW-PSM, as a direct method, providing a simple way to identify relevant price points and

consumers' price sensitivity, has found broad interest in research in evaluating PS for new technologies (Khandker & Joshi, 2018; Steinbrenner & Turcinkova, 2021; Stopka et al., 2018; Larson, 2014) as well as in business practice as a reference for price setting for new technologies and services (Sadwick, 2020).

Measuring PS of consumers and understanding its drivers is crucial in Marketing as well as Economics, since it has a direct impact on profitability, customer satisfaction and the relevance of cost factors for the consumers' purchase intention (Ramirez & Goldsmith, 2009).

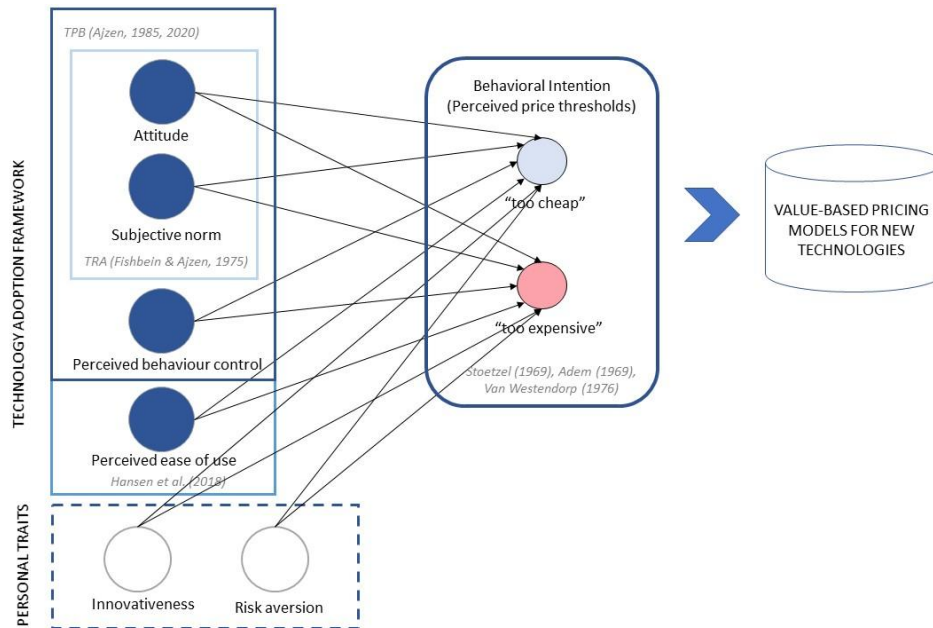
But what drives perceived threshold prices and PS? Based on the vW-PSM, this study aims to explore what shifts the distribution of perceived maximum or minimum price levels, relying on arguments from theories of acceptance of new technologies. Technology acceptance theories are essential to assess the successful investment in disruptive technologies. A multitude of models, based on information structure, psychology and sociology have been proposed (theory of reasoned action, theory of planned behaviour, technology acceptance model, unified theory of acceptance and use of technology), which all aim to explain human behavioural intention. For a review of models used in the field of Marketing, see for instance Venkatesh et al. (2003).

We make use of the theory of planned behaviour (TPB) as theoretical arguments for our study, which dates back to Ajzen (1985) and has been extensively studied over the years (Ajzen, 1991, 1996, 1996, 2002, 2006, 2011, 2020; Ajzen & Sheikh, 2013). As emphasized by Ajzen (2020), the understanding of consumers' response to disruptive technologies is crucial for the implementation of interventions that allow the demand to be met. In this context, TPB increases again in prominence when it comes to exploring the intention to acquire new technological products or services. The TPB assumes that an increase in the intention related to the target of purchasing a particular technology is positively related to the actual purchase event and determined by three factors: attitude towards the conduct or behaviour, subjective norm regarding the behaviour and perceived behavioural control. Following the reasoning by Seol et al. (2016), the three beliefs which form the TPB are part of the groundwork of technology adoption models and other theories (like the unified theory of acceptance and use of technology and its antecedents). Moreover, with the focus on motivational factors (attitude, subjective norm) as well as non-motivational elements like control over the behaviour, it is not only aligned with other technology adoption theories from marketing research but also with the economic theory of motivated beliefs (Bérnabeau & Tirole. 2016). Hence, TPB constitutes an

appropriate and simple framework for the analysis of psychological determinants of perceived price thresholds for new technologies.

TPB has been successfully used to explain and predict behaviour in a multitude of behavioural domains (Azjem, 2020); examples include its application to physical activity (Hagger et al., 2002), smoking cessation (Hukkelberg et al., 2014) or dietary choice (McDermott et al., 2015) and in many cases to the study of technology acceptance (Azjem, 2020), which is the case here. Moreover, TPB has found application to understand value assessment by consumers, measured in terms of willingness to pay as the highest price consumers are willing to pay for a product or service (Sánchez et al., 2018). However, considering the potential of TPB to explain price sensitivity as latent construct, we find ambiguous results. On the one hand, Bhutto et al. (2022) find a positive effect of PS on purchase intention as well as a moderating effect of PS on the relation between attitude and purchase intention and between subjective norm and purchase intention. Similar, Hsu et al. (2017) identify a positive effect of PS on purchase intention and find that a higher PS strengthens the relationship between all the TPB elements and purchase intention. Furthermore, Dorce et al. (2021) find a moderating effect of price sensitivity in the relation between behavioural intention and actual behaviour. On the other hand, Brandão and Gonçalves da Costa (2021) identify PS as an antecedent of attitude and perceived behaviour control. This is understood as evidence of complexity of the relation between PS and motivational concepts that drive technology adoption. In this context, a direct approach explaining perceived price thresholds is expected to provide additional insights.

Figure 1 Conceptual framework



Included in the groundwork of technology adoption theories is the concept of the *subjective norm (SN)*, that is, the social influence. The subjective norm is one of the key elements of TPB, having its origin in the theory of reasoned action, as one of the most influential theories to explain individual acceptance of technology (Venketesh et al., 2003; Fishbein & Ajzen, 1975). The concept captures the social pressure in terms of others approving a considered behaviour and/or whether it is important that others perform a certain behaviour (Ajzen, 2020; Fishbein & Ajzen, 1975). This social opinion can arise in different formats. For instance, Kostyra et al. (2016) find that online consumer reviews reduce the influence of price in consumers’ purchase choice, which leads us to establish our first hypothesis. In the same line, Talebian and Mishra (2018) find that peer-to-peer communication influences consumers’ willingness to pay for autonomous vehicles. Finally, Dominique-Ferreira et al. (2020) show that the social opinion, measured in terms of star ratings for the case of hotels, affects the psychological acceptable price range as defined by van Westendorp and consequently their price sensitivity. Moreover, Ponzoa et al. (2021) find, in the context of technology adoption by the generations of “Digital Natives”, that subjective norm and value perception are the strongest predictors of purchasing AR glasses, however, this is not true in the same way for 3D printers. Altogether, this leads us to the expectation that the subjective norm also influences the

price thresholds of the acceptable price range for disruptive technologies, which is formulated in the following hypothesis:

Hypothesis 1: Subjective norm influences the acceptable price range.

H1a. Subjective norm has a direct influence on the price which is perceived as “too cheap”.

H1b. Subjective norm has a direct influence on the price which is perceived as “too expensive”.

The second key element, which drives behaviour beliefs with respect to the adoption of new technologies, is an individual’s *attitude (ATT)*, in terms of personal appraisal of a behaviour. It includes aspects such as beliefs held about the likely consequences or other attributes of the behaviour (Fishbein & Ajzen, 1975). If the appraisal is positive, the TRA suggests that the behaviour intention is higher. Furthermore, the literature suggests that attitude provides a link to the perceived value theory (Seol et al., 2016; Kim & Kankanhalli, 2009). Hence, it is identified as a relevant factor in consumers’ value assessment of technologies, addressing the challenge of value quantification. This leads us to the hypothesis that attitude influences the perceived threshold prices which define the acceptable price range.

Hypothesis 2: Attitude (ATT) influences the acceptable price range.

H2a. Attitude has a direct influence on the price which is perceived as “too cheap”.

H2b. Attitude has a direct influence on the price which is perceived as “too expensive”.

Beyond the motivational factors (subjective norm and attitude), the *perceived behaviour control (PBC)*, which refers to the ease or difficulty in the performance (Seol et al., 2016; Ajzen, 1991), is considered relevant for consumers’ behaviour with respect to the new technologies. TPB explains behaviour by taking into account the intention, context and temporality of the action. In relation to intention, the stronger the intention, the more likely it is to perform the behaviour (e.g. to buy a certain technology). However, intention is not enough, as it is conditioned by other factors such as the time to perform the behaviour or the availability of economic resources. The possibility of overcoming these impediments depends on the existence of facilitating factors (previous experience or help from third parties). Therefore, the greater the individual’s control over the

behaviour, the more likely it is that the intention will be carried out (Fishbein & Ajzen, 2010), that is, the idea that the ability of people to fulfil their intentions depends on their perception to control factors that may facilitate or prevent the intended behaviour, hence keeping control (Ajzen, 2020). That is, although you may have an innovative positive attitude towards the technology and a social environment strengthening this intention, a low control belief may lead you to abandon your intention. In the context of determining price sensitivity, we consider the related construct of decision closure, which refers to the ability to perform a particular behaviour, and which has been identified in previous literature as driver of price sensitivity. Concretely, Lee et al. (2020) find that consumers with higher need for closure, in terms of desire for a quick solution (which is positively associated with a high power distance belief) are less inclined to search for better offers, which implies that they are less price sensitive, which leads us to hypothesize:

Hypothesis 3: Perceived behaviour control (PBC) influences the acceptable price range.

H3a. Behaviour control has a direct influence on the price which is perceived as “too cheap”.

H3b. Behaviour control has a direct influence on the price which is perceived as “too expensive”.

Fourth, we consider the *Perceived ease of use (PEOU)*, as a variable from the TAM, as a potential determinant of consumers’ price sensitivity with respect to disruptive technologies. The TAM model is an alternative to TPB, which appeared in the late 1980s (Davis, 1987); it is linked to information systems and analyzes how users accept and use a new technology. The model has been widely used in recent years to analyze the acceptance of telemedicine (Kamal et al., 2020), to measure the use of Zoom (distance learning system) in language courses (Alfadda & Mahdi, 2020), to validate the acceptance of mobile libraries (Rafique et al., 2020), to test the use of gamification in higher education (Vanduhe et al., 2020), and to measure satisfaction with mobile applications (Talantis et al., 2020). There are a number of factors that influence how and when people will use the new technology, especially PEOU, perceived usefulness and perceived enjoyment. Malatji et al. (2020) have analyzed the use, modifications and limitations of the model and suggest the possibility of extending it in line with what is proposed by

authors such as Legris et al. (2003) with the inclusion of variables such as change processes, or in other words, innovation models.

Taylor and Todd (1995) propose a combined model which unifies TAM and TPB using the four predictors: Attitude, Subjective Norm, Perceived Behaviour Control and Perceived Usefulness. However, Hansen et al. (2018) show that it is the TAM variable Ease of Use which interacts with TPB variables, concretely, ease of use amplifies the effect of perceived behavioural control. Hence, we hypothesize that, in addition to the introduced TPB predictors, PEOU will influence consumers' acceptable price range for disruptive technologies.

Hypothesis 4: Perceived ease of use (PEOU) influences the acceptable price range.

H4a. Ease of use has a direct influence on the price which is perceived as “too cheap”.

H4b. Ease of use has a direct influence on the price which is perceived as “too expensive”.

Considering previous findings on price sensitivity as a latent variable in the context of the framework of a technology adoption, Natarajan et al. (2017) identify personal innovativeness, perceived risk, satisfaction and intention to use as direct determinants of price sensitivity, which leads us to consider also personal traits as potential drivers of the acceptable price range of disruptive technologies.

There are several studies analyzing the relationship between innovativeness and price sensitivity, concluding that there is a clear relation between both variables in the process of technology assessment. For instance, Munnukka (2005) finds that customers' level of innovativeness explains significantly the customers' levels of price sensitivity for mobile customer services. Innovators seem to be less price sensitive than later buyers (Goldsmith & Newell, 1997), which justifies the marketing practice of skimming the market for a new product by charging high early prices as a way of generating larger early profits to offset development costs. That is, innovators are less concerned about prices. In the same line, Goldsmith et al. (2005) identify innovative consumers to be relatively more price insensitive than other consumers. Others argue that adoption of new technologies can be understood as a signal of being an innovative person (Shalev & Morwitz, 2012). Finally, Erdmann et al. (2021) find that innovativeness has a direct effect on consumers' purchase intention of augmented reality smart glasses.

Bringing it all together, this leads us to the hypothesis that innovativeness also has an impact on consumers' perceived price thresholds.

Hypothesis 5: Being innovative influences the acceptable price range.

H5a. Innovativeness has a direct influence on the price which is perceived as “too cheap”.

H5b. Innovativeness has a direct influence on the price which is perceived as “too expensive”.

Furthermore, the market introduction of new technologies is expected to be associated with a risk for the retailer as well as a risk for consumers, in terms of perceived product risk or behavioural risk. However, there is little research on the relationship to price variables. Qin and Xue (2010) find that the retailer's risk aversion and the price sensitivity of demand are two factors that negatively impact supply chain performance. Considering strategic price setting, Zheng et al. (2017) show that the risk aversion variable impacts price sensitivity, reducing the optimal price. From a consumer perspective, the product risk has been considered in several technology adoption studies (e.g. Baccarella et al., 2020; Nataraja, 2017), however the relation to value perception is sparse. Seol et al. (2016) argue that the acquisition of new technologies is commonly associated with a certain risk, which may negatively affect the perceived value in the decision whether to adopt the technology. Hence, we set up the hypothesis that consumers' risk aversion influences their perceived acceptable prices.

Hypothesis 6: Risk aversion influences the acceptable price range.

H6a. Risk aversion has a direct influence on the price which is perceived as “too cheap”.

H6b. Risk aversion has a direct influence on the price which is perceived as “too expensive”.

To sum up, after the analysis of the theoretical framework and the presentation of the hypotheses, Table 1 provides an overview of the contribution of the present study, embedded in the literature on the assessment of disruptive technological products.

Table 1. Contribution to the literature on the assessment of disruptive technological products

Disruptive Technological products and services	Authors	Technology acceptance considerations						Price/Value considerations		Ground theory/ Direct measurement model	
		Theory of planned behaviour			Complementary constructs			Perceived Value	Willingness to pay/ Acceptable prices		Price sensitivity
		Attitude	Subjective norm/ social opinion	Perceived behaviour control	Perceived ease of use	Innovativeness	Risk/ Fear				
Self-driven car technology	Baccarella et al. (2020)				✓		✓			Technology acceptance model	
3D printer, AR technology	Parzoo et al. (2021)	✓			✓			✓		Technology acceptance model	
ARsmartglasses	Erdmann et al. (2021)	✓			✓	✓		✓		Value-based adoption model	
Hybrid-vehicles	Bhutto et al. (2022)	✓	✓	✓						Theory of planned behaviour	
Mobile office	Seol et al. (2016)	✓	✓	✓			✓	✓		Theory of planned behaviour	
Mobile shopping apps	Nataraja (2017)				✓	✓	✓			Extended technology acceptance model	
Noise pollution in road transportation	Sánchez et al. (2018)	✓	✓	✓				✓		Extended theory of planned behaviour	
Self-driven car technology	Elvik (2020)							✓		Willingness-to-pay estimation	
4G Service	Khandker & Joshi (2018)							✓	✓	Van Westendorp price sensitivity model	
Mobility as a Service (MaaS)	Stopka et al. (2018)							✓	✓	Van Westendorp price sensitivity model	
Electric vehicle	Larson (2014)							✓	✓	Van Westendorp price sensitivity model	
ARsmart glasses, 3D printer, self-driven car technology, robotics mobility	This paper	✓	✓	✓	✓	✓	✓	✓	✓	Theory of planned behaviour (TPB) to explain consumers' perceived price threshold (Van Westendorp) for disruptive technological products.	

3. Methodology and data

3.1. Van Westendorp price sensitivity model

We make use of the Van Westendorp price sensitivity model (Van Westendorp, 1976), as a direct pricing method, which has recently found prominence once again when it comes to determining prices for new service technology (Steinbrenner & Turcinkova, 2021; Dominique-Ferreira et al., 2019; Khandker & Joshi, 2017; Ceylana et al., 2014). This method is very frequently used for innovative technology products, such as 4G, electronic cars, and Maas (mobility as a service) (Stopka, 2018; Larson, 2014), which allow a boundary to the final sales price to be established, which can be a reference for the firm's pricing decision, especially when it comes to investment in new technologies with uncertain returns. Hence, renowned research companies, such as GfK, are also using this analysis for new and relaunched products in Europe (Hahsler, 2015).

To measure price sensitivity, we use the four van Westendorp questions, adopted from Khandker and Joshi (2018), to identify the individual price perceptions of being “too cheap”, “cheap”, “expensive” or “too expensive”. As illustrated in Figure 2, the graphical representation of the cumulative distribution of the response for each question allows to determine the acceptable price range for the technology under analysis as illustrated. The

intersection points of “too cheap” (inverted) and “getting expensive” is defined as the point of marginal cheapness (PMC) and the intersection point of “too expensive” and “inexpensive (bargain)” (inverted) is defined as marginal expensiveness (PME). Here it is important to highlight that the outer levels of the individually perceived acceptable price points (“too cheap” and “too expensive”) have also been used by other value-based pricing methods (Stoetzel, 1969; Adam, 1969).

In order to make the vW-PSM metric of price sensitivity comparable across technologies, we follow Steinbrenner and Turcinkova (2021), who suggest to divide the identified price range by one of the reference price points to provide relative measures. The relative range of acceptable prices is defined as $RROAP = (PME - PMC)/PME * 100\%$, and the relative range between Indifference point and Optimal price is defined as $RGIO = (IDP - OPP)/IDP * 100\%$, such that the means score is $MSRV = (RROAP + RGIO) / 2$.

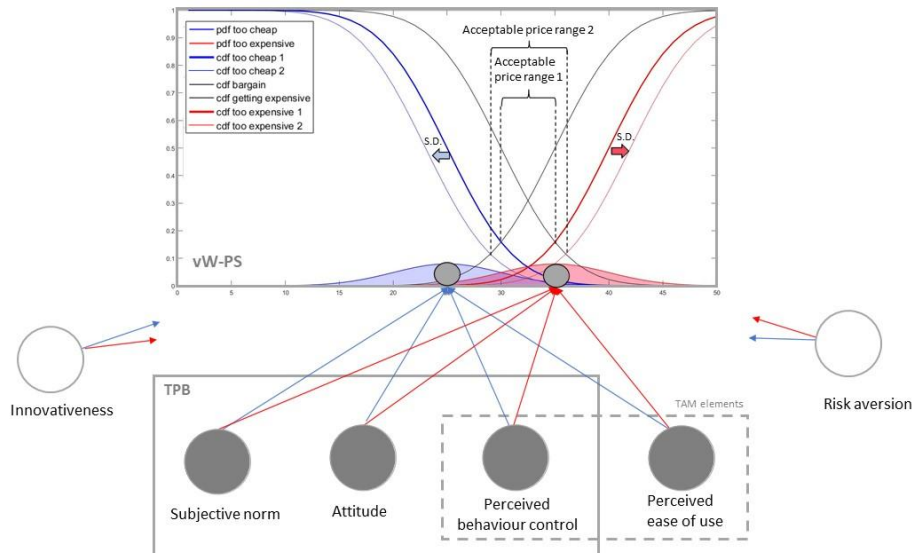
3.2. Determinants of the acceptable price range

To verify relevant differences in price sensitivity across consumer types, which can be addressed using appropriate advertising messages, we use the concept of stochastic dominance. Considering the determinants of the TPB (ATT, PCB, SN), PEOU and personal traits (innovativeness, risk aversion), we follow the argument by Bloch and Manceau (1999, 2020) that any advertising campaign [triggering the corresponding variable], makes consumers more favourable towards the advertised product. That can translate into a shift in the price distribution F to a distribution G which is stochastically dominant, increases the price range and consequently reduces the price sensitivity. Hence, considering different behavioural beliefs of consumers, first-order stochastic dominance (FOSD) of the cumulative price distribution of the maximum price consumers of a certain type are willing to pay, implies an increase in the acceptable price range and hence a reduced price sensitivity, *ceteris paribus*.

In order to explore how the main drivers for technology adoption or price sensitivity impact the acceptable price range, we use a structural approach. Considering relevant constructs from the literature on planned behaviour in the context of technology adoption, a structural approach applied to the van Westendorp variables allows what drives the perception of people of acceptable minimum and maximum prices to be determined and hence shifts the cumulative price distribution and consequently influences consumers' price sensitivity (Figure 2).

Figure 2 Structural model

How behavioural beliefs may determine consumers' acceptable price range



We use a PLS-SEM approach to explore how the main drivers for technology adoption or price sensitivity impact the acceptable price range and hence can be leveraged to influence price sensitivity.

The use of PLS-SEM for the analysis of complex consumer behaviour has grown considerably in recent years in applied explorative research in Marketing (Hair et al., 2019) and has also attracted the interest of economic financial research (Ramli et al., 2018). For the analysis of the proposed model, as illustrated in Figure 2, it is considered the most appropriate estimation method, given that PLS-SEM shows a good performance for small sample sizes with almost no restriction on the data (Hair et al., 2013), which is especially relevant for data from laboratory experiments. Moreover, given the predictive purpose of technology adoption and pricing, PLS-SEM allows a predictive approach to be combined with confirmatory factor-based analysis (Sarstedt et al., 2021). These convenient features for explanation and predictions have given rise to the recent incorporation of the PLS-SEM methodology in software packages like Stata, which is frequently used by economists (Venturini & Mehmetoglu, 2017), and facilitates addressing the incorporation of attitudinal and motivational variables in the decision analysis of consumers.

In the context of our paper, the structural analysis is considered complementary to the direct pricing model. Considering the relevant constructs, which we identified from the literature on planned behaviour of technology adoption, a structural approach applied to the perceived critical price thresholds allows shifts in consumers' perception of acceptable minimum and maximum prices to be identified. That is, cumulative price distribution curves (as illustrated in Figure 2 by the blue curve for the perceived minimum price and the red curve for the perceived maximum price) may shift as a result of triggering the identified constructs.

3.3. Data

We use data from an experiment at Lab ESIC Tech, a university space where undergraduate students of Business Administration, Marketing Studies and Communication Studies at a Spanish private university experimented with five different technologies and a random sample of students were subsequently asked to fill out a web-based questionnaire, based on adopted validated scales for each of the components (McLean & Wilson, 2019; Shalev & Morwitz 2012; Mandrik, 2005).

The experiment was organized in the framework of an educational innovation project to approach students to the use of new technologies through direct experience. For this end, 830 undergraduate students visited in groups of 7 students the laboratory where they were exposed sequentially to the different technologies. Students experimented with two types of augmented reality smart glasses (HoloLens from Microsoft and Magic Leap), a 3D printer, the Segway robot, participated in a demonstration of the Scribit robot and a presentation of self-driven car technology.

Based on the 253 complete responses, valid responses have been defined based on the transitivity requirement (i.e., being consistent in terms of too cheap \leq cheap (bargain) \leq getting expensive \leq too expensive).

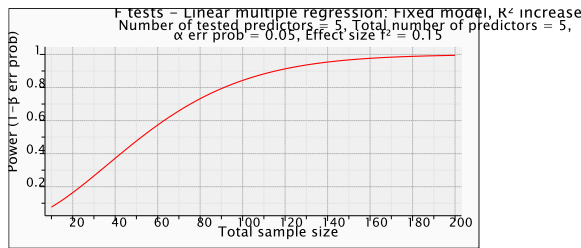
Table 2. Valid responses by technology

Technology	ARSG	3d printer	Self-driving car	Segway robot	Scribit robot
Responses that fulfil the transitivity criteria	141	173	169	178	162

For the questionnaire we adopt and adapt validated scales from previous research. In order to verify the relationship between measurement of the critical price perception thresholds, we conduct a discriminant validity analysis using the Heterotrait-Monotrait criteria (HTMT) with the cross-construct correlations being in the interval [0.421, 0.591] and hence lower than the suggested maximum level of 0.9 (Henseler et al., 2015), which is evidence enough that the items of the critical vW-PSM thresholds discriminate.

Respective the sensitivity of the results with respect to the sample size, we perform a power analysis, as suggested by Hair et al. (2019). We use the GPower 3.1 software to perform an F-test which provides the necessary sample size to achieve different levels of statistical power (Faul et al., 2007). As suggested by Cohen (1988), a power of at least 0.8 is sufficient to obtain accurate results. Figure 3 illustrates the power as function of the sample size, which confirms that our valid responses for all the technologies analyzed (N={ 141, 173, 169, 178, 162 }) guarantee a power of at least 0.95.

Figure 3 Power analysis



4. Results

Table 3 reports the Van Westendorp price points for all the technologies, which shows difference in the acceptable price range across the analyzed technologies. To make the results comparable across technologies, the standardized vW-PSM measures are provided. The relative range of acceptable prices, as a normalized measure of PS, differs across technologies, being the highest for augmented reality smart glasses (ARSG), followed by 3D printers and the lowest for the hoverboard robot (Segway robot).

Table 3 Van Westendorp price points and standardized vW-PSM measures

<i>Price points vW-PSM</i>	Technology price perception (in EUR)
----------------------------	--------------------------------------

	ARSGS	3D printer	Self-driving car	Segway robot	Scribit Robot
Point of marginal cheapness (PMC)	250	350	25000	6000	200
Point of marginal expensiveness (PME)	550	750	45000	8000	400
Optimal price point (OPP)	380	525	30000	6500	300
Indifference price point (IPP)	400	528	40000	6600	320
Indifference price - optimal price	20	3	10000	100	20
Range of acceptable pricing	250-550	350-750	25000-45000	6000-8000	200-400
<i>Standardized vW-PSM measures</i>					
$(PME - PMC)/PME$	0.5455	0.5333	0.4444	0.2500	0.500
$(IDP - OPP)/IDP$	0.0500	0.0057	0.2500	0.0152	0.0625

Figure 4 illustrates the van Westendorp price sensitivity graph for the considered technologies. Furthermore, we provide a radar chart for a visual comparison of standardized price sensitivity by technology.

Figure 4 Van Westendorp price sensitivity graphs by technology



For AR technology, we find that the acceptable price range is 250–550 EUR, that is, while consumers would consider a price higher than 550 EUR as too expensive, a price lower than 250 EUR would likewise imply a considerable loss of potential consumers but for the reason that they would doubt the quality of the product. Furthermore, we find that the optimal price point (OPP), where the too cheap and too expensive price distribution lines intersect, is about 18%, which means 82% of the participants think that when the price is about 380 EUR, they think that it's neither too expensive nor too cheap. The

indifferent point (IDP) is identified at 400 EUR, which implies that at this price the number of consumers who think the price is too high is equal to the number of persons who view it as being good value.

For 3D printing products, the acceptable price range is 350–750 EUR, which is larger compared to the AR technology. The optimal price point is 525 EUR, with 89% of the participants considering this price neither too expensive nor too cheap. However, the indifferent point is 520 EUR, such that the difference between IDP and OPP is equal to the AR technology.

For self-driving car technology, the acceptable price range is 25,000 to 45,000 EUR, the OPP is 30,000 EUR, corresponding to 89.5% of the participants and its IDP is at 40,000 EUR.

For the Segway robot, compared to the other technologies, the acceptable price range is relatively tight, between 6,000 to 8,000 EUR. The OPP is 6500, very close to the point of marginal cheapness as the lower bound of the acceptable price range.

For the scribit robot we identify an acceptable price from 200–400 EUR, and the optimal price point is 300 EUR. The IDP is 320 EUR, just 20 euros below the OPP.

Considering the exploratory analysis of what drives the identified price ranges, Table 4 reports the estimated path coefficients of the structural model analysis, which has been estimated using the SmartPLS software package.

Table 4 Estimated path coefficients

	Path coefficient (p-value in brackets)				
	ARSGS	3D printer	Self-driven car	Scribit Robot	Segway Robot
Subjective norm → Pmin (too cheap)	0.111 (0.025)	0.148 (0.082)	0.150 (0.019)	0.064 (0.238)	0.121 (0.012)
Subjective norm → Pmax (too expensive)	-0.072 (0.168)	0.072 (0.215)	-0.086 (0.156)	0.025 (0.402)	0.235 (0.003)
Attitude → Pmin (too cheap)	0.024 (0.366)	0.016 (0.426)	-0.010 (0.463)	0.185 (0.055)	-0.028 (0.316)
Attitude → Pmax (too expensive)	0.051 (0.227)	0.129 (0.166)	0.066 (0.270)	0.103 (0.188)	-0.152 (0.065)
PBC → Pmin (too cheap)	0.062 (0.169)	0.290 (0.001)	0.147 (0.029)	0.314 (0.000)	0.223 (0.003)
PBC → Pmax (too expensive)	0.169 (0.010)	0.022 (0.404)	0.212 (0.007)	0.153 (0.076)	0.150 (0.036)
EOU → Pmin (too cheap)	-0.127 (0.070)	-0.166 (0.166)	0.082 (0.205)	-0.086 (0.188)	0.018 (0.421)
EOU → Pmax (too expensive)	0.080 (0.212)	-0.132 (0.201)	0.130 (0.105)	0.148 (0.087)	0.155 (0.083)
Innovativeness → Pmin (too cheap)	0.166 (0.021)	-0.041 (0.315)	0.015 (0.455)	0.038 (0.382)	0.094 (0.231)

Innovativeness → Pmax (too expensive)	0.050 (0.308)	-0.207 (0.113)	0.117 (0.211)	-0.100 (0.274)	0.082 (0.295)
Risk aversion → Pmin (too cheap)	0.127 (0.157)	0.144 (0.175)	0.035 (0.347)	0.154 (0.213)	0.281 (0.154)
Risk aversion → Pmax (too expensive)	0.026 (0.387)	0.237 (0.128)	-0.136 (0.219)	0.061 (0.343)	0.012 (0.441)

It is worth noticing that executing the same analysis on the full sample, including respondents which didn't comply with the requirement of consistent price perceptions (transitivity), the results are robust with two exceptions: Applied to the full sample before data cleaning, *Innovativeness* has a significant effect on the perception of the minimum price for all technologies analyzed, while the effect of *EOU* on the perceived maximum price level for the robotic technology is not significant.

5. Discussion and Management Implications

Price sensitivity can be influenced by the investment in advertising (Mela et al., 1997), brand management (Baumert & de Obesso, 2020) and information disclosure strategy (Bar-Isaac et al., 2012). In order to provide actionable insights for management how to trigger the identified relevant variables of vW-price sensitivity, we organize the results under the following aspects:

(i) Those variables that will widen the acceptable price range, either towards the maximum price or the minimum price, thus reducing price sensitivity.

Impact on perceived price levels	Impact on price sensitivity
Decreases Minimum Price	Reduces price sensitivity
Increases Maximum Price	

(ii) Those variables that will narrow the acceptable price range, either towards the maximum price or the minimum price, thus increasing price sensitivity.

Impact on perceived price levels	Impact on price sensitivity
Increases Minimum Price	Increases price sensitivity
Decreases Maximum Price	

Table 5 Overview of results for management implications

	H1	H2	H3	H4	H5	H6
	Subjective Norm	Attitude	Perceived Behavioural Control (PBC)	Perceived Ease of Use (PEOU)	Innovativeness	Risk Aversion

AR Smart Glasses	Increases Minimum Price	Not Significant	Increases Maximum Price	Decreases Minimum Price	Increases Minimum Price	Not Significant
3D Printer	Increases Minimum Price	Not Significant	Increases Minimum Price	Not Significant	Not Significant	Not Significant
Self-driver Car	Increases Minimum Price	Not Significant	Increases Minimum Price and Maximum Price	Not Significant	Not Significant	Not Significant
Scribit Robot	Not Significant	Increases Minimum Price	Increases Minimum Price and Maximum Price	Increases Maximum Price	Not Significant	Not Significant
Segway Robot	Increases Minimum Price and Maximum Price	Decreases Maximum Price	Increases Minimum Price and Maximum Price	Increases Maximum Price	Not Significant	Not Significant

We identify ease of use as variables that allows the acceptable price range to be increased through an increase in the maximum price (Hypothesis H4b), hence reducing price sensitivity. For the AR Smart Glasses, triggering the perceived Ease of Use, decreases the price level which is still accepted to be of sufficient quality, and hence increases the acceptable price range. Likewise, for the robotic technology (Scribit robot and Segway robot), an increase in perceived ease of use triggers an increase in the maximum price level consumers are willing to pay, increasing the acceptable price range.

Behavioural control is also identified as increasing the perceived maximum price (Hypothesis H3b), however, it is also found to raise the perceived minimum acceptable price, which can partially or completely eliminate the increase in the interval of acceptable prices. For AR Smart Glasses, Scribit Robot and Segway Robot technologies, managers may reduce the price sensitivity increasing the acceptable maximum price, by creating stimuli evoking the need for closure, which is in line with the argument of Lee et al. (2020), but it should be controlled for a possible simultaneous change and magnitude in the minimum acceptable price which may outweigh the expected effect and translate into a shift of the acceptable price range to higher levels.

Furthermore, we identify four variables that allow price sensitivity to be increased, reducing the acceptable price range. First, an increase in the social pressure (subjective norm) goes along with an increase in the minimum price for all considered technologies (except scribit robot), which, keeping everything else constant, reduces price sensitivity in the sense of van Westendorp (Hypothesis H1a). Note that this is in line with the

findings by Kostyra et al. (2016) that online reviews reduce the relevance of the price in the decision making. Moreover, the results complement the findings from the literature of value-based adoption of AR smart glasses, which identifies social pressure as one of the main drivers to be enhanced for a successful implementation (Erdmann et al., 2021). We thus contribute to previous studies on the different effects of the use of social pressure within communication strategies (Haenschen, 2016) and in particular on the synergies that occur when social pressure and marketing efforts are combined for the adoption of new technologies (Risselada et al., 2014).

Second, the attitude towards robotics technology (Scribit Robot, Segway Robot) is found relevant to reduce the acceptable price range, either through an increase of the minimum acceptable price or a decrease of the maximum price consumers are willing to pay (Hypothesis H2). This confirms the link of attitude and consumers' perceived value, as suggested by Seal et al. (2016), which is not only relevant for adoption but also for pricing of the new technology, which are both necessary for a successful introduction of new technologies into the market.

Third, perceived behavioural control in general is identified to push the minimum acceptable price to higher levels. Given that the control belief may be determinant in pursuing the intended behaviour or abandoning the idea (Ajzen, 2020), this suggests that perceived control may be understood as a quality device, which would explain the increased minimum acceptable price level, that is, below this price, consumers expect not to be provided with the desired control level.

Fourth, innovativeness increases the acceptable minimum price only for augmented reality smart glasses (Hypothesis H5a), but in general, the results suggest that the personal traits innovativeness and risk aversion have no significant effect on the acceptable price range of the considered disruptive technologies.

When allowing for non-consistent responses respective the perception of different price levels (full sample), the indicated results are robust but interestingly personal traits become relevant. Concretely, for all technologies studied, innovativeness becomes a relevant driver of the perception of the minimum price, which is interpreted as innovative people having a sense that disruptive technologies require a certain price level to deliver the expected quality. For the considered transportation technologies (Self-Driver Car and Segway Robot), risk aversion becomes an important factor increasing the minimum price level consumers consider as acceptable (below they would consider the technology of insufficient quality).

Note that all these results contribute to a better understanding of consumers' response to disruptive technologies with the purpose to implement the right interventions to respond to the demand (Ajzen, 2020). During the mental process of product evaluation and finally the product choice by the consumer, consumers have plenty information at hand, which can be used to trigger the identified psychological determinants of price sensitivity as part of the price communication strategy. For the implementation, considering the main channels consumers use to gather price information: e-commerce, marketplace, price comparison websites (Erdmann et al., 2020), or general communication channels (social networks, emailing, etc.) the use of appropriate communication in the product description or/and through consumer reviews are expected to yield the identified effect on price acceptance and price sensitivity. Concretely, firms may develop a communication campaign based on the relevant behaviour beliefs of consumers, in particular, highlighting the ease of use of the technology, what others could think of a person when buying this technology, or highlighting, for example, the autonomy and total control of the consumer in the purchase decision, we could influence the price range that is considered acceptable for each technology, that is, develop a pricing strategy driven by the behaviour beliefs of consumers with respect to disruptive technologies.

Moreover, in line with the suggestions by Bénabou and Tirole (2016), we argue that the identified psychological aspects that reflect consumers' beliefs should be treated as economic assets, which can be managed through the information input consumers have access to. Given that consumers have often only partial knowledge on products and services, Bar-Isaak et al. (2010, 2012) highlight that firms have different information strategies at hand to influence consumers in their value assessment: use an opaque strategy directed at the whole market; use a transparency policy directed at consumers who have a high valuation; use an intermediate marketing strategy with clients incurring some (search) costs to gather relevant information. Given the heterogeneity across the considered technologies, a segmentation of the communication strategy is recommendable. Moreover, with the increasing use of zero party and first party data in the development of marketing strategies for new technologies, additional factors may show up relevant and may allow to extend the proposed model and/or be used directly for the segmentation of the communication strategy by consumer segment.

At the same time, the identified attributes may induce the firm to realize selective investment in product or service attributes to boost the perception of key elements in consumers' evaluation process (Bar-Isaak et al., 2012), with the target to shift the price intervall or/and influence price sensitivity.

A limitation of the insights we can derive from the study is that the analysis is based on intended behaviour not on actual behaviour (e.g. Dong et al., 2020). Furthermore, we have focused on elements of the TRA, TPB and TAM to explain changes in consumers' vW-PS; however, especially for disruptive technologies, the brand dimension is also expected to be relevant in the price perception and price sensitivity (Guyt & Gibijsbrechts, 2017), but would require a variety in suppliers of the analyzed technologies. A further limitation to be considered is that the sample of respondents is upper-middle class university students from a European university and the results could differ for other income classes or cohorts.

Finally, note that the outlined perspective of behavioural beliefs influencing consumers' intended behaviour and price perceptions is in line with the economic perspective by Bénabou and Tirole (2016), who recently developed the theory of cognitive motivation. While traditionally in economics consumers were assumed to process information rationally and generate utility from functional and leisure values, recent theories on motivated reasoning fill this gap considering consumers' intentionality, which can rationalize observed behaviour.

6. Conclusion

This research bridges the gap between the identification of psychological drivers of price perception and the identification of concrete price boundaries, through a joint consideration of the theory of planned behaviour and the van Westendorp price sensitivity model, providing actionable insights how behaviour beliefs can determine consumers' perceived price thresholds, which allows to trigger consumers' price sensitivity for particular technologies.

Methods of perceived value pricing find increasing application for disruptive technologies (Steinbrenner & Turcinkova, 2021), which allows to test consumers' price perception before going on the market. At the same time, explorative studies have been carried out what drives perceived value or price sensitivity of technologies (e.g. Seol et

al., 2016; Bhutto et al., 2022). In this context, the knowledge or awareness on the relationship between motivational beliefs and perceived price thresholds by consumers may overcome some barriers of adoption of these disruptive technologies (which may be perceived as too expensive or too cheap to deliver the expected value) through an appropriate communication strategy, which allows to influence consumer's perceived threshold prices and hence their price sensitivity.

We conclude that there are significant differences in the price sensitivity for different disruptive technologies and the variables that drive the minimum and maximum acceptable price by consumers. In general, the variables that will help us most to reduce price sensitivity in emerging technologies are perceived behavioural control and perceived ease of use, while variables such as innovativeness, subjective norm and attitude allow higher levels of acceptable minimum prices to be triggered and consequently increase the vW price sensitivity.

Thus, when planning our business strategies (price positioning), marketing (product positioning and target segmentation) and communication (communication insight), we may trigger these variables in order to increase or reduce the price sensitivity of the emerging technologies, depending whether we consider a price increase or decrease, with the aim to boost revenues and business growth.

This research is just the first step towards a unified approach to pricing of disruptive technologies motivated by established theories of technology acceptance. For future research, we consider it worthwhile putting the findings of this paper into practice by carrying out communication campaigns with different combinations of the identified variables that drive price sensitivity, and by means of a/b testing to check whether they effectively generate higher or lower price sensitivity of the technologies studied. Another line worth exploring is the consideration of socio-demographic variables on the drivers of price sensitivity or consider geographical and cultural differences in the assessment of disruptive technologies (e.g. perceived price thresholds for service robots in Europe versus China), which would allow for segmentation. Finally, another possible extension of the present research would be to analyze different moments of maturity of a technology, based on the Gartner hype cycle, to study the relevance of the identified drivers of price perception over time.

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