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Persuasion in sustainable entrepreneurship: The role of electronic word-of-mouth and the elaboration likelihood of signals in reward-based crowdfunding for sustainable technology products.

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PREFACE

I would like to take the opportunity to briefly express my deep gratitude and begin with the educational institution, highlighting the extraordinarily supportive attitude of Dorian Proksch and Charlotte Röring. In addition, I would like to pay my sincerest regards to my family and the invaluable support of my brother and my aunt Maria. I would also like to denote my deepest appreciation to my partner Duong, who has blessed me with unimaginable commitment and encouragement irrespective of the difficulties. Finally, I would like to end the acknowledgements with the following dedication:

in memoriam Heinz-Josef

ABSTRACT

In an era of digitalization, electronic word-of-mouth (eWOM) and crowdfunding share similarities in the way they disrupt existing paradigms. Alike eWOM, crowdfunding resolves conventional limitations and incorporates social information in its process of empowering consumers. Both phenomena advance the democratization of entrepreneurship with the ability to co-create innovative endeavors and, in the case of crowdfunding, even commercialize them without traditional financial intermediaries. The similarity of reward-based crowdfunding to the scenario of online purchasing constitutes a central aspect in their interconnection. Electronic word-of-mouth may serve as an instrument for consumers to overcome information asymmetries and limited expertise in their purchase decision-making. It is particularly critical in the context of sustainability since respective attributes are more difficult to measure and verify. This study empirically confirms eWOM's relevance in sustainable entrepreneurship by sampling technology products from Kickstarter and analyzing them through the lens of the Elaboration Likelihood Model and the theory of signaling – thereby contributing to an emerging stream of literature and leading academic discourse.

Keywords: (reward-based) crowdfunding, Elaboration Likelihood Model (ELM), electronic word-of-mouth (eWOM), signaling, sustainability, sustainable entrepreneurship

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List of abbreviations

ABBREVIATION	MEANING	TRANSLATION
AMO	Ability-Motivation-Opportunity	
ANOVA	analysis of variance	
AUD	Australian dollar	
B2C	Business-to-Consumer	
C2B	Consumer-to-Business	
C2C	Consumer-to-Consumer	
CAD	Canadian dollar	
CAGR	Compound Annual Growth Rate	
cf.	cōnfer	compare with
CHF	Swizz francs	
CLT	Central Limit Theorem	
CN	China	
DE	Germany	
DV	dependent variable	
e.g.	exemplī grātiā	for example
EDT/ECT	Expectation and (Dis-)Confirmation Theory	
ELM	Elaboration Likelihood Model	
EO	Entrepreneurial Orientation	
et al.	et aliī (m, m&f) / et aliae (f)	and others
etc.	et cētera	and so forth
EU	European Union	
EUR	euro	
ES	Spain	
eWOM	electronic Word-Of-Mouth	
GBP	Great British pound	
HKD	Hong Kong dollar	
HSM	Heuristic-Systematic Model	
i.e.	id est	that is

ABBREVIATION	MEANING	TRANSLATION
IAM	Information Adoption Model	
IPO	Input-Process-Output	
IV	independent variable	
JPY	Japanese yen	
KBV	Knowledge-Based View	
LET	Language Expectancy Theory	
MLP	Multi-Level Perspective	
NEA	National Endowment for the Arts	
NL	The Netherlands	
NPD	New Product Development	
OLS	ordinary least squares	
RBV	Resource-Based View	
SEK	Swedish krona	
SGD	Singapore dollar	
SME	Small- and Medium-Sized Enterprise	
TAM	Technology Acceptance Model	
TBL	Triple Bottom Line	
TPB	Theory of Planned Behavior	
TRA	Theory of Reasoned Action	
UK	United Kingdom	
UN	United Nations	
US / USA	United States of America	
USD	United States dollar	
UTAUT	Unified Theory of Acceptance and Use of Technology	
VIF	variance inflation factor	
viz.	vidēlicet / vidēre licet	that is to say, namely
WCED	World Commission on Environment and Development	

1. INTRODUCTION

Marking the beginning of the paper, this incipient section addresses the frame and focus of the study. The introduction provides initial information on the background and context of the topic and discusses its relevance and aims in the practical and theoretical sphere. In addition, this chapter briefly delineates the structure of the paper.

1.1 BACKGROUND

Since the public initiation of the Internet, the world has been subject to paradigm changes throughout many spheres of life. May it be communication and self-expression, economical transactions, sociopolitical activism, or the overarching legal framework that has continuously been adapted in order to regulate the ever-growing technological advancements. Digitalization bears opportunities for not only already established actors but it has also allowed space for disruptions from the bottom up. Two phenomena that have fundamentally affected the aforementioned examples are electronic word-of-mouth (eWOM) and crowdfunding.

The ascent of e-commerce was accompanied with a rise in uncertainty, changes in available cues and hence asymmetric information. Customers were no longer able to physically examine the quality indicators of an offering due to the computer-mediated nature and were therefore exposed to a one-sided control over which information are provided (Wessel et al., 2016). However, novel media channels, often interchangeably titled albeit not universally agreed as 'Web 2.0' or 'social media' (Constantinides & Fountain, 2008), have fostered a change in the inquiry, creation and distribution of online information (King et al., 2014). Consumers themselves have taken an active role in relationship management, becoming content producers and engaging participants in B2C/C2B as well as C2C interactions (Hennig-Thurau et al., 2010). Consequently, eWOM can serve as a means of overcoming the distortion of information control (e.g. Park & Lee, 2009; Manes & Tchetchik, 2018) and reflects consumer empowerment. The effect on customers' decision-making process has been so substantial that it is argued that the majority of consumers rely on electronic word-of-mouth as informative signals in their purchasing behavior and that many are actually affected in their choices (Cheung & Lee, 2012; Cheung & Thadani, 2012). Further, turning the conventional marketer-to-consumer monologue into a multi-directional approach has not only been deemed more impactful (Bickart & Schindler, 2001) but has also introduced a new level of value co-creation (Payne et al., 2008) and innovation (Bhimania et al., 2019). Digitalization has strongly elevated existing concepts on one hand, e.g. by providing user communities with online platforms to accelerate as an innovative force, and has also opened new doors on the other, by, for instance, progressing innovative co-creation into an era of user-accessible, alternative entrepreneurial financing (Brem et al., 2019, Ryu & Kim, 2016).

Whereas electronic word-of-mouth empowered smaller actors in already unprecedented ways, the onset of crowdfunding effectively democratized the landscape of entrepreneurship altogether. The access to weak ties through the help of technology exhibits several similarities between eWOM and crowdfunding. However, the obvious difference in the latter consists in the emphasis to also gain tangible benefits when drawing upon these relatively unknown peers. In other words, crowdfunding capacitates entrepreneurs to collect monetary resources without the need of traditional financial entities (e.g. banking institutions, venture capitalists) and may come in the form of donations, loans, equity or rewards (Mollick, 2014; Zaggl & Block, 2019). Accordingly, consumers' inclusion evolved considerably. Intangible contributions, such as the exchange of information, ideas and knowledge that has been accreted as well as moderated by types of eWOM (Candi et al., 2018), transformed the norms of new product development (NPD) typically by extending an established firm's prevalent internal processes with consumers' input (Poetz & Schreier, 2012; Zhang et al., 2020). Crowdfunding goes beyond and allows campaign creators to gather both immaterial and material provisions. While the latter may be less of an incentive for established businesses, which often seek other benefits in the use of crowdfunding (e.g. Brown et al., 2017), the access to financial means reduces the barriers of market entry for entrepreneurs distinctly (Kraus et al., 2016). Considering the example of user innovation through user communities (Baldwin et al., 2006), crowdfunding thus advances consumers' ability in generating new product ideas by resolving pecuniary limitations and being able to commercialize these themselves (Brem et al., 2019). As such, consumers ascend in their role as entrepreneurial stakeholders and constitute a critical dependency for project realization (Valančienė & Jegelevičiūtė, 2014).

The similarities between eWOM and crowdfunding are profound and the interconnection between both is relevant in multiple ways. First, both share contextual factors such as the Internet-based democratization of the constructs they disrupt and their ability to overcome conventional geographical boundaries accordingly (cf. Cheung & Lee, 2012; Mollick, 2014). Second, social aspects are critical components in both phenomena and a prosocial theme is recognizable in matters such as social influence (cf. Cheung & Thadani, 2012; Kuppuswamy & Bayus, 2017) and the strong element of community (cf. Belleflamme et al., 2014; De Valck et al., 2009). In fact, one of the very few papers that study eWOM in the field of crowdfunding, argues social information to be essentially embedded in the crowdfunding act and enable overcoming its obstacle of asymmetrical information (Shneor & Munim, 2019). While in particular social media are known for their use in marketing, including the field of crowdfunding, the archetype has expanded to comprise co-creation and innovation as it powers entrepreneurial endeavors (Olanrewaju et al., 2020).

The interplay of electronic word-of-mouth and crowdfunding is also relevant in the area of sustainability. With a continuously increasing audience that is propelled through platforms for user-generated content, attention towards environmentalism has gained prominence. In academic publishing, sustainable entrepreneurship has emerged beyond the presence in limited special issues with the establishment of dedicated journals and an exponential growth of articles releasing (Terán-Yépez et al., 2020). Throughout its evolution, various terms and derivatives with more (e.g. green/eco entrepreneurship, social entrepreneurship) and less (e.g. corporate social responsibility (CSR)) mutuality evolved into a consensus of three central elements sought to be balanced: social, environmental and economic factors (e.g. Anderson, 1998; Bento et al., 2019b; Choi & Gray, 2008; Terán-Yépez et al., 2020). In line with the notion that entrepreneurial activities are difficult to finance through traditional channels, social and environmental foci derogate conventional funding attractiveness even further due to a diminution of financially measurable outcomes (Calic & Mosakowski, 2016). Consequently, crowdfunding represents an alternative financing opportunity since funding sustainable ventures is predominantly based on non-conventional methods (Choi & Gray, 2008) and sustainable businesses are driven by innovation (Schaltegger & Wagner, 2011). Considering the growth of sustainability-oriented crowdfunding campaigns, research is lagging behind and thus called upon, especially empirically (Petruzzelli et al., 2019). This study could be the first to empirically explore the bridging of additional information asymmetry in sustainable, reward-based crowdfunding campaigns with the help of electronic word-of-mouth.

Overall, the evolvement of user-generated content and its relevance in modern economics has accrued an extensive stream of literature that exemplarily includes networking and relationship management, information and knowledge exchange, co-creative innovation, and marketing (Olanrewaju et al., 2020). Yet, the outcome of electronic word-of-mouth is typically not measured in immediate financial terms despite its linkages to firm performance (Franco et al., 2016; Paniagua & Sapena, 2014). The direct economic impact of crowdfunding, on the other hand, is known to be substantial, even if valuations and forecasts may vary considerably, and its rapid growth is expected to continue (Mordor Intelligence, 2020; QY Research, 2020). Accordingly, the pertinence of crowdfunding has also been recognized by academics, who spotlight crowdfunding as a driver of digital, innovative and social entrepreneurship among others (Wehnert et al., 2019).

Altogether, digitalization has caused radical adjustments in the dynamics of innovative value creation and corresponding processes (Nambisan et al., 2017). Firms understood to leverage the crowd's involvement and deliberately delegate tasks (Hinings et al., 2018) in what could also be questioned as an evolutionary, relative form of outsourcing – or at least a double-edged sword that poses also obstacles for entrepreneurs the more established actors enter their respective field (Brown et al., 2017). With the intertwined topics being presented, the next subsection sets forth the research direction and underlines its relevance.

1.2 OBJECTIVE AND RELEVANCE

Over the years, reward-based crowdfunding has been receiving a thriving stream of research and its prevalence is unambiguously acknowledged (e.g. Cordova et al., 2015; Mollick, 2014). A common denominator in this context of entrepreneurship literature is often the look at the largest reward-based crowdfunding platform in the United States, Kickstarter (Kuppuswamy & Bayus, 2017). Despite Kickstarter's expansion in the categories and types of campaigns offered, the platform still highlights the centrality of creative endeavors. In its mission statement, Kickstarter explicitly emphasizes "art and creative expression" (Kickstarter, PBC, 2020b), whereas a competitor like Indiegogo places "Get the tech" as its first words on its "About" page (Indiegogo, Inc., 2020), respectively. Also, Kickstarter actively promotes creative efforts in its marketing, for instance in the form of its newsletters or even by dedicating an integrated website with its own Chrome browser extension (Kickstarter, PBC, 2020a) to publish artists' stories. Compared with the official public institution for supporting artists in the United States, the National Endowment for the Arts (NEA), Kickstarter surpassed the agency's entire public funding volume for creatives already in 2012, which is just three years after Kickstarter's inception (Mollick & Nanda, 2016). Due to its market positioning and reputation, research on crowdfunding has therefore often been granted attention in this direction. The investigation into technology products, however, does not appear proportional, considering that even Kickstarter lists technology as the third most funded category in terms of monetary contribution (Kickstarter, PBC, 2021) as well as with regard to the assertion that more than half of China's crowdfunding industry is said to fall under this category (Wang & Yang, 2019). China has become a major driver of global crowdfunding growth (Liang et al., 2019) with some market reports going as far as declaring it the largest global player altogether (e.g. QY Research, 2020). As a consequence, it appears an adequate field of interest.

Moreover, the ratio of successfully funded projects gives further reason for the examination of technology products. Kickstarter statistics (Kickstarter, PBC, 2021) show on first glance that the overall level of successfully completed campaigns (i.e. approximately 38%) signifies room for improvements. Older figures stated by Mollick (2014) as well as Zhao et al. (2017) disclose though that the rate even decreased from previously 48% and 43% respectively. While the Chinese reward-based crowdfunding market exhibited a relatively similar rate as Kickstarter, namely approximately 35% in 2015 (Wang & Yang, 2019), the number for Indiegogo differs substantially as Zhao et al. (2017) report the ratio to be around 10% at the time. Making matters worse, a closer look reveals that the success rate differs heavily by category. For instance, based on Kickstarter figures of 2017, Liang et al. (2019) report successful funding of approximately 60% of theater as well as 53% of comics campaigns, whereas technology projects barely reach 20%. Although Kickstarter's current numbers indicate an improvement for comics (i.e. approximately 60%), theater and technology remain almost unchanged. Consequently, more research into the field of crowdfunded technology products may foster better results for the accumulating number of campaigns in this area.

Accentuating the request for additional research corroborates when narrowing down the category of technology to the inclusion of sustainability as a contextual factor. Innovative developments are needed to solve environmental dilemmas of the present age without impairing the lives of future generations (Terán-Yépez et al., 2020). Striving for seminal solutions with the help of technological advancements is a logical inference and visible in academic publishing devoting whole journals to the topic, e.g. Journal of Cleaner Production. Innovative implementations of sustainability in technology projects may come in the groundbreaking function of the product itself. Albeit the more common tenor rather addresses the attributes of a product and its handling throughout the supply chain, e.g. sourcing of materials or the fulfillment of certified norms (Wehnert et al., 2019). Next to the regular uncertainties that exist in crowdfunding, social and environmental claims of sustainable projects are intricate to ascertain (Petruzzelli et al., 2019). This decrease in the ability to verify the propositions is due to the added complexity and intangibility, and causes additional information asymmetry that has not been researched within the sustainable crowdfunding setting yet (Wehnert et al., 2019). In succession to the emerging perception that eWOM vanquishes the distorted control of information in crowdfunding, this paper is to examine whether signaling of electronic word-of-mouth persists in the sustainable context, too.

With reference to e-commerce, legal systems have generally become a solid base for economic transactions to take place and feature protective clauses for both parties involved in the trade. Astonishingly, the situation differs in the context of crowdfunding, in which the fulfilment of any reward offered is often not unequivocally acknowledged by law (Mollick, 2014). Moreover, even if the creator of the campaign indeed delivers the reward, the output may deviate from what was originally advertised. The risk of none-delivery as well as the uncertainty of the actual quality supplied underlines the meaning of informative cues, such as eWOM, to help consumers form a decision. In other words, crowdfunding rewards are alike experience goods insofar that the actual merit of a product can only be assessed upon receipt of the good (Nelson, 1970; Wessel et al., 2016). Contrariwise, the choice of product category opposes this analogy to some extent because technology products typically resemble search goods in that their specifications are commonly listed, e.g. in a data sheet, and can therefore be evaluated in advance as long as they are made publicly available (Bi et al., 2017). Nevertheless, uncertainty remains due to possible discrepancies in the end result, based on feasibility issues of an ambitiously innovative campaign for instance, and also due to their rather high complexity. In addition, product type represents one of many moderators not sufficiently reflected in existing research, especially in terms of sustainable crowdfunding as the article of Wehnert et al. (2019) appears to be the sole study that investigates in this direction albeit using product complexity as a moderating variable instead. The decision to focus this paper on technology goods therefore parallels as a constraint to not further complicate the moderating variables.

When it comes to theories present in existing literature, signaling (Ross, 1977; Spence, 1973) features a notable appearance in the fields of both electronic word-of-mouth (e.g. Cheung et al., 2014) as well as reward-based crowdfunding (e.g. Lagazio & Querci, 2018). On top of this groundwork a very limited number of papers apply the Elaboration Likelihood Model (ELM) from Petty and Cacioppo (1986) to study signals in reward-based crowdfunding from a perspective of persuasion – namely those by Allison et al. (2017), Bi et al. (2017), Liang et al. (2019) and Wang and Yang (2019). However, none of them focus on sustainability. The applicability of ELM is reasoned by viewing the reward-based crowdfunding act as a scenario of purchase decision-making that includes the persuasion elements of advertising and information processing (Wang & Yang, 2019). Moreover, Bi et al. (2017) describe ELM as a pivotal theory in the domain of marketing communication and provide the only study that combines the topic of eWOM and crowdfunding on the theoretical backgrounds of ELM and signaling. Although the study constitutes a valuable contribution, it has limitations that provide reasons for further investigation. These include an oversimplified research model and limited attention towards moderating factors. Further reason consists in culture. Three out of the four previously mentioned studies are set in a Chinese (Bi et al., 2017; Wang & Yang, 2019) and Taiwanese (Liang et al., 2019) background with only one western counterpart in form of US-based Kickstarter projects (i.e. Allison et al., 2017). Research on the impact of culture in both eWOM (e.g. Luo et al., 2014) and crowdfunding (e.g. Cho & Kim, 2017) highlight moderating effects, which in themselves serve as justification for this paper's undertaking even if the study of Bi et al. (2017) was otherwise identical.

Another subject to consider consists in manipulated electronic word-of-mouth. Findings in the hotel (Mayzlin et al., 2014) and restaurant industry (Luca & Zervas, 2016) disclose the presence of fraudulent reviews across different online platforms and industries. Schwieren and Weichselbaumer (2010) suggest that parties that contend with better-performing competitors exhibit a higher probability to manipulate. Illegitimate behavior in crowdfunding was pointed out by Wessel et al. (2016) regarding false quantitative social information. The authors accurately reason in their study that fraudulent Facebook Likes do not equal supplemental activity within the social network because the Likes do not disperse when based on fake accounts. The point where the study falls short, however, consists in the thought that only those visitors of the campaign are being influenced by the inflation of Likes, that already intended to invest in the first place. The lack of data on the backers themselves and the conventional limitations of research focus are hence an invite for further investigation. In other words, it would be relevant to contextually understand how the potential backers that are exposed to social information in the crowdfunding environment are processing the attempt of persuasion, which may also give insight as to when backers are responding negatively (i.e. ignoring social information) or positively (i.e. engaging in word-of-mouth or simply invest).

Eventually, the ambition of this study may be guided by the following research question:

- What role does electronic word-of-mouth play in the decision-making process in crowdfunding sustainable technology products, seen as signals from a dual-process perspective?

1.3 OUTLINE

Rounding off the introductory chapter, a brief outline for the rest of the paper is provided. The research commences with a comprehensive literature review in the second chapter. Within this review, the phenomena of electronic word-of-mouth and crowdfunding are defined and existing literature on these topics elaborated. Complementary, a description of sustainable entrepreneurship is given. Afterwards, the literature examined is used to deduce hypotheses that are integrated into a research model. Both chapters together are to provide theoretical answers to the research questions. The fourth chapter then describes the methodological background with which statistical and descriptive results as well as their analysis are produced in the chapter to follow. The look at the data is extended into the sixth and final chapter, which provides a conclusion to the research question, offers insights into the implications of the results for both, theory and practice, and ends with limitations of the study as well as suggestions for further research.

2. LITERATURE REVIEW

With the aim to contribute to an emerging stream of academic literature, this chapter delves into already existing research. Current literature is studied to gather relevant knowledge and generate an understanding of the matter. A preamble is compiled in form of a synopsis on accumulated research perspectives. Further subsections define the subjects of electronic word-of-mouth and crowdfunding and establish the context of sustainability.

2.1 PRELIMINARY RESEARCH OVERVIEW

In a matter of understanding the research topic in its breadth, a preliminary but extensive literature review took place. It constituted the first of two phases of assessing existing research, which in itself can be divided into identifying and analyzing literature (Cheung & Thadani, 2012). For identification, the database search provider ScienceDirect (Elsevier B.V., 2020) served as the primary access point. The in-/ and exclusion choices of articles focused on the distinction of peer-reviewed, academic research articles from reputable journals, as such are thought to be highly influential (Podsakoff et al., 2005). Additional attention was given to impact, including simple metrics such as citations (e.g. Crossref (Publishers International Linking Association, Inc., 2020)) and advanced trackers such as Altmetric (Digital Science & Research Solutions Ltd., 2020). Also, theoretical versus empirical contribution was considered along with implications.

Central keywords included electronic word-of-mouth or eWOM, Elaboration Likelihood Model or ELM, crowdfunding or reward-based crowdfunding, signal or signaling, and sustainability or sustainable entrepreneurship. The search was executed across domains, which is also suggested for this context of entrepreneurship (Olanrewaju et al., 2020), and keywords were applied from broad to specific during the process. After screening, more than 200 articles were selected for a closer look. The goal of the preliminary literature review was to encompass the phenomena from different angles in order to get a more complete representation and to ascertain relevant research opportunities (Bhimania et al., 2019). Also, such thorough approach may help with content validity later due to overall better comprehension of the topics at hand. Since the scope of this paper does not allow a holistic elaboration of the reviewed literature, Table 15 (see appendix) at least serves as a non-exhaustive overview of theories across various disciplines. Further integration into this paper is determined by relevance as well as contextual benefit as long as time and scope allow.

2.2 ELECTRONIC WORD-OF-MOUTH (eWOM)

The subject of social communication has been well-established over decades of research throughout an extensive body of literature. In the incipience of it Hovland (1948) characterized social communication as a sequence in which a communicator exerts influence over a recipient through interaction. In specific, traditional word-of-mouth involves verbal exchange between two informal parties about commercial topics such as goods and brands (Cheung & Lee, 2012; Wessel et al., 2016). As a consequence, the speaker and the listener are required to be present at a specific time and place in order to interact with each other in person. In such direct setting, both sides can draw on abundant indicators regarding contextual and social parameters, especially since these usually private exchanges are based on existing personal relationships (King et al., 2014).

Already in the analog era, word-of-mouth has been known to be of larger influence on purchase decision-making than conventional marketing (Day, 1971). Customers have been affected by such information regarding services and products from various industries in both short- and long-term (Bone, 1995; Herr et al., 1991). According to Arndt (1967) this even applies to the dispersion of new products and this finding may thus serve as an early indicator that word-of-mouth plays a role in entrepreneurial endeavors, alike those relevant in crowdfunding. The impact of word-of-mouth may in part be reasoned by an increase in credible cues available since they are not marketer-created but rather from fellow consumers (Brown et al., 2007). Such external inducements can also be seen as a form of social influence, in which particularly the personal connection exhibits high leverage on potential customers (Arndt, 1967; Cheung & Thadani, 2012). Therefore, the persuasion of conventional word-of-mouth depends not only on the content of the stimulus but also on the reputation of the individual broadcasting (King et al., 2014).

With reference to an ongoing digitalization, word-of-mouth has transcended into an online presence. Whereas conventional socializing comes with physical limitations, electronic word-of-mouth exceeds traditional boundaries of time and space (Duan et al., 2008). It addresses a virtually unlimited audience and abrogates geographical paradigms with the help of the Internet. Modern connectivity has therefore facilitated consumers to interact with each other at an unprecedented capacity and caused a persistent transformation of how information is exchanged (Olanrewaju et al., 2020; Wessel et al., 2016). It thereby elevates the interpersonal setting to a level of mass media while maintaining persuasive elements (Wathen & Burkell, 2002). It does so also due to its infinite nature since a digital message theoretically continues to exist indefinitely and its asynchronous character reaches a larger audience (Godes & Mayzlin, 2004). In accordance, electronic word-of-mouth can be described as information about commercial topics that are expressed by customers that were, are or will be involved with the respective subject and who share their insight with the help of the Internet regardless of its valence (Hennig-Thurau et al., 2004). This social information can be made available in both qualitative or quantitative form that is easy to generate and share (Cheung et al., 2014).

The conventional idea of word-of-mouth can still be applied to modern communication as illustrated in the framework of Cheung and Thadani (2012), in which the five integral factors are comprised of the broadcaster, the content, the audience, the context, and the accompanying effect. However, previously close ties built on strong relationships have been superseded with the Internet's ability to connect to a network of lesser known peers from various backgrounds (King et al., 2014; Olanrewaju et al., 2020). Consequently, the computer-mediated communication of word-of-mouth impedes the ability to evaluate source credibility (Huang et al., 2012). Chaiken (1980) separates and disregards the content from the sender in this form of credibility, which is commonly portrayed as how much the communicator can be believed or trusted and how competent the individual is perceived (Luo et al., 2014). The former, i.e. trustworthiness, is a relevant factor in social communication and bears impact on persuasion (Hovland & Weiss, 1951). On the topic of credibility Wathen and Burkell (2002) focus on the three primary elements (i.e. source, stimulus, audience) and picture credibility with many facets and countless combinations of interactions between them. Notwithstanding, research has shown that weak ties are not inferior per se and are sources of influence that otherwise would not be accessible (King et al., 2014).

Over the years, even digital channels have gone through changes in how information is shared and networks are formed. Common examples include forums, review sites, blogs and an ever growing number of platforms categorized as social networking sites (Cheung & Lee, 2012). Social media is characterized by its online-based foundation on Web 2.0 and being a powerful tool for user-created content (Kaplan & Haenlein, 2010). These novel channels disrupted how consumers inquire, generate and distribute information (King et al., 2014). Despite the fairly anonymous environment, consumers are able to locate rather unknown peers with similar interests, whose electronic word-of-mouth is typically easy to reach (Kozinets et al., 2010). Extending one's personal network through these new channels of media enabled consumers to organize themselves in networks previously impossible and resulted in the dissemination of social information in the digital sphere (Wessel et al., 2016). It also has raised electronic word-of-mouth to not only exhibit more impact than marketer-created information (Bickhart & Schindler, 2001), just like its conventional counterpart (Day, 1971), but also to become among the most influential data available online overall (Duan et al., 2008).

The active involvement of customers transformed business operations (e.g. customer relationship management) since consumers are no longer only receivers but are also generating and sharing the content themselves (Hennig-Thurau et al., 2010). In the shift away from a one-directional flow consumers have thus become proactive partners in not only B2C/C2B but also C2C communication and represent drivers of influence within their valuable networks (Blazevic et al., 2013; Hennig-Thurau et al., 2010; Hoffmann & Novak, 1996). Some scholars even go as far to state that any public attention is rather positive due to the benefits of awareness (Berger et al., 2010; Duan et al., 2008). This notion may be supported by studies that single out the amount of reviews as a sales driver while rejecting the relevance of valence (e.g. Liu, 2006). However, this view is not undisputed since the tendency towards negativity and resistance to concede is a known bias in psychological research (Skowronski & Carlston, 1989). In electronic word-of-mouth, the strength of a personal relationship is argued to moderate the direction of a message in that closer relationships are more likely to be balanced (i.e. two-sided: positive and negative), whereas the exchange with weaker ties tends towards negativity (King et al., 2014). The impact of negative eWOM is also argued to be higher, especially in case of experience goods (Park & Lee, 2009; Yin et al., 2016). Although the power of negativity does not hold true for cases of intense emotionality and therewith irrationality (Kim & Gupta, 2012), eWOM is still argued to appeal better to consumers' emotions than traditional marketing (Bickart & Schindler, 2001). Additionally, it takes more established platforms for consumers to follow upon positive eWOM whereas negative statements are effective regardless of platform (Lee & Youn, 2009; Park & Lee, 2009).

According to Buckland (1991), the meaning of information is relevant if it supports the reduction of uncertainties. In line with that, Brynjolfsson and Smith (2000) denote that providing more data leads to a decrease in uncertainty which in turn results in an increase of consumers' disposition to spend. Since the engagement in informative communication is a central part of social media (Olanrewaju et al., 2020), its enormous growth has offered a fruitful platform for electronic word-of-mouth to reach large audiences at a higher and faster rate (King et al., 2014). Interestingly, a substantial amount of Instagram users is in fact subscribed to commercial profiles of firms, and business pages on Facebook are widespread (Olanrewaju et al., 2020).

Early research in conventional word-of-mouth accentuated involvement as the key motive for engagement – divided into product, personal gain, altruism and marketing (Dichter, 1966). Throughout continuous research the baseline has remained fairly stable with additional research confirming and extending the keywords, such as Sundaram et al. (1998), who append emphasis on the inquiry of advice, among others. Altruism is a recurring theme in both studies and also explained by Yoo et al. (2013), who highlight the urge for participants to help fellow consumers in their purchase decisions. Namely those who seek to overcome the distorted access to information, according to King et al., 2014. The authors also argue that engaging in electronic word-of-mouth is driven by the desire to lower efforts in acquiring and evaluating information in purchase decisions and the risk that comes with it. In the eyes of Cheung and Thadani (2012), involvement generally reflects the priority of the subject as well as how relevant it is to the person.

With the rise of electronic word-of-mouth also spawned illegitimate practices. In case of the manipulation of eWOM, studies found its existence across different online platforms. Mayzlin et al. (2014) indicated that smaller, independent players in the hotel business are more likely to participate in faking reviews and that this is done more often on less strict platforms such as TripAdvisor.com compared to Expedia.com. The tendency of smaller actors to commit fraud is also supported by the study on restaurant reviews on Yelp by Luca and Zervas (2016), while economic psychology research (Schwieren & Weichselbaumer, 2010) underlined that parties struggling to keep up with competition in terms of performance are more likely to take advantages illegitimately. Overall, such unethical conduct creates misleading information and biases that may result in misjudgments or even mistrust among the audience and hence inferior decision-making (Mayzlin et al., 2014; Luca & Zervas, 2016). Considering that such manipulation undermines credibility (Luca & Zervas, 2016) and causes severe negative effects (Wessel et al., 2016), it only adds more relevance to research as it hinders overcoming information asymmetry.

Research into eWOM expanded across fields over the years. Nowadays, electronic word-of-mouth is well-acknowledged as a marketing tool but more recently is also investigated for its role in entrepreneurship regarding the process of innovation and co-creation (Bhimania et al., 2019; Olanrewaju et al., 2020). The Internet-based nature of eWOM substantially lowers the financial resources necessary in involving and serving customers (King et al., 2014). The ability to connect and mobilize consumers across various backgrounds allows entrepreneurs to access their social capital (Olanrewaju et al., 2020). Hence, multi-directional communication on open platforms fosters the sharing of knowledge and ideas that influences new product development by contributing to previously predominantly internal processes (Candi et al., 2018; Poetz & Schreier, 2012; Zhang et al., 2020). An empirical study by Kuhn et al. (2016) about entrepreneurs in rural areas in the U.S. indicates that consulting weak ties, e.g. through social media, can indeed positively affect business growth. Considering that only a single digit percentage of small- to medium-sized firms is said to utilize social media strategically on their quest for innovations (Olanrewaju et al., 2020), crowdfunding may present the opportunity to change that.

2.3 CROWDFUNDING

Scientific literature on crowdfunding has quickly arisen from a state of scarcity to a continuously aspiring topic that has already gained considerable attention throughout a multitude of disciplines. Its stage of diverse viewpoints is accentuated by its multifaceted character (Lagazio & Querci, 2018; Roma et al., 2017). Crowdfunding has grown at an exponential rate and emerges as a recognizable instrument to finance entrepreneurial endeavors and non-profit projects (Shneor & Munim, 2019). The impact crowdfunding has in economic terms and also its relevance in innovation has caused politics and media to seize the topic, as well (Cordova et al., 2015). The remarkable force with which crowdfunding moves forward is exemplified by the Jumpstart Our Business Startup Act from 2012, which represents larger, relevant legislative changes in a leading economy (i.e. U.S.A.) just three years after Kickstarter's foundation (Roma et al., 2017). Hence, the phenomenon has established itself in the theoretical and practical spheres alike.

Literature identifies crowdfunding as a concept that originates from crowdsourcing (Belleflamme et al., 2014; Bi et al., 2017; Cho & Kim, 2017; Shneor & Munim, 2019). The latter is known as a method of outsourcing critical business activities to the public online in which the collaboration is designed to help the inquiring firm at no or low costs (Kleemann et al., 2008). The definition of the former, i.e. crowdfunding, has evolved subtly with scholars rather refining recurring definitions to include its ongoing expansions over time. Petruzzelli et al. (2019) depict that persisting elements of crowdfunding comprise of the following five: creators, investors, campaign, platform, output. Frequently cited examples of definitions refer to Schwienbacher and Larralde (2010) and Belleflamme et al. (2014). The perhaps most established and inclusive description however comes from Mollick (2014), who avoids narrowing down the forms of crowdfunding since it allows for further growth without the need of incremental revisions. Instead the scholar defines crowdfunding to base on a fairly extensive amount of online peers who participate with rather small investments in order to realize entrepreneurial efforts with economic, social or cultural ambitions and doing so independently of conventional financial entities. Further, crowdfunding can be described as a micro-lending approach to crowdsourcing in that it adds the pecuniary element (Cho & Kim, 2017; Cordova et al., 2015). Seen from a stakeholder-based view it can also be delineated as an instrument that links entrepreneurs to fairly-unknown investors (Valančienė & Jegelevičiūtė, 2014).

In spite of varying approaches on classification, crowdfunding can commonly be divided into two denominations, i.e. investment and non-investment (e.g. Shneor & Munim, 2019) or alternatively named incentive-based and donation-based (e.g. Bretschneider & Leimeister, 2017), and includes four categories in total that consist of equity, lending, donations and rewards (e.g. Kraus et al., 2016). All forms are available to non-commercial individuals as well as businesses. The only exception lies in equity-based campaigns, which naturally require a contractual arrangement with a corporate entity in order to acquire a stake. Participants in equity crowdfunding hence own a part of the business they invest in, which may include eligibility for a share of the profits the venture may achieve (Mollick, 2014). This method is particularly relevant in cases where business ideas are expected to do extraordinarily well (Belleflamme et al., 2014). Campaigns that feature lending mechanisms presume the redemption of the loan and may offer interest as a potential remuneration (Kraus et al., 2016). Donation-based crowdfunding is a special form in that the only return of investment, if any, consists in social attributes and thus it turns investors into patrons (Shneor & Munim, 2019). Projects that operate reward-based typically seek financing in exchange for goods or other non-monetary, (im-)material compensation (Mollick, 2014). The preservation of ownership represents a central reason for entrepreneurs that seek commercialization (Bento et al., 2019b). Correspondingly, it is recognized as a dominant form of crowdfunding and its pre-market offering provides a unique characteristic (Belleflamme et al., 2014; Shneor & Munim, 2019). Its prevalence is also shown in the fact that it was said to comprise the most available platforms (Kuppuswamy & Bayus, 2017).

Estimates of the global crowdfunding market differ drastically depending on source. An agency that is often referenced in literature is Massolution. According to their publications, the global market exhibited a volume of 1.5 billion US dollars in 2011 (Cordova et al., 2015; Kim et al., 2017), 16 billion US dollars in 2014 (Cho & Kim, 2017; Roma et al., 2017; Wessel et al., 2016) and 34 billion US dollars in 2015 (Brown et al., 2017; Wang et al., 2017). Opposing examples based on other sources are a market size of 262 billion Euros in 2016 (Shneor & Munim, 2019) or the forecasts by the World Bank of 90 billion US dollars in 2020 (Petruzzelli et al., 2019) and surpassing 300 billion US dollars by 2025 (Allison et al., 2017). A web search outside of scientific literature also provides inconclusive results and hence it appears more sensible to fall back on official figures from the platform itself. In 2017, Kickstarter disclosed the total amount pledged to be nearly 3 billion US dollars (Liang et al., 2017). The amount more than doubled to approximately 6.3 billion US dollars four years later, i.e. by 2021 (Kickstarter, PBC, 2021). The contributions base on ca. 13 million (2017) vs. ca. 20.4 million (Δ+ ca. 57%, 2021) investors, of which ca. 4 million (2017) vs. ca. 6.8 million (Δ+70%, 2021) are recurring backers. So, the ratio of those backers that follow up on previous pledges approximates a third.

Whereas the reported numbers of Kickstarter may appear promising for creators of any size, Belleflamme et al. (2014) note that many campaigns fall short. Statistics regarding the rate of success or failure were previously elaborated in the introductory chapter. As laid out, the number of successful projects decreased over time (Kickstarter, PBC, 2021; Mollick, 2014; Zhao et al., 2017). Additionally, the chances are lower depending on the category a campaign falls under. This is particularly obvious in the case of technology projects, as previously discussed. The category in fact falls off as the least successful category on the leading U.S.-based platform and barely improved compared to statistics from 2017 reported by Liang et al. (2019). The trend is interesting also because it stands in contradiction to the notion that products are more attractive in the realm of funding (Cordova et al., 2015). Furthermore, the predicament for investors is emphasized by legal deficiency. Although national actors have advanced the formalities that crowdfunding acts on, investing in reward-based campaigns still bears no universal guarantee to actually receive the purchased goods or their quality at receipt (Mollick, 2014). Adding to it, Mollick (2014) states that the time of delivery increases by funding level. On the other hand, Kickstarter lowers the financial risk for investors by restricting the scheme to an approach of all-or-nothing (Cumming et al., 2020). This means that customers are not charged for their chosen investment as long as projects do not reach their required goal, which helps to attract a larger audience (Zvilichovsky et al., 2017). Furthermore, Kickstarter says it screens projects before airing them with reference to their compliance with the platform's criteria, which also is said to include legal matters, and can be perceived as another measure of risk reduction (Petruzzelli et al., 2019). The process remains questionable without the disclosure of proper auditing, however.

According to Valančienė and Jegelevičiūtė (2014), crowdfunding can be further characterized by its ability to financially incentivize consumers and advance their role as entrepreneurial stakeholders. The ambition towards the realization of a project becomes especially apparent by the discovery of Zvilichovsky et al. (2017). The authors highlight that approximately a third (/fifth) of the successful campaigns of their extensive sample achieves funding only by the contribution of at most three (/one) average investor(s). A typical growth rate for an average project with a duration of 30 days consists in two to three investors a day which adds perspective to its meaning (Kuppuswamy & Bayus, 2017). The results are also in line with the findings of Mollick (2014) who exposits that 75% of the investigated campaigns that succeeded have attained a surplus amount by only 10% of their target. Thus it can be concluded that campaigns are likely to succeed by small margins. In the study of Cordova et al. (2015), who sampled technology projects, the results were drastic in that already a raise of one percent in targeted funding level results in a decrease of campaign performance by five to six times. On the other hand, those projects that make it past 30% funding within the first week of the campaign succeed 90% of the time (Kuppuswamy & Bayus, 2017). Hence, funding targets are sensitive levers and critical for the success of a campaign (Cordova et al., 2015; Mollick, 2014). Moreover, the individual importance of backers clearly reflects a discrepancy to traditional markets (Britterl & Schreier, 2018). At the same time, however, it should be noted that the passion of realization is shared among the peers and that the community is an essential trait (Brem et al., 2019; Britterl & Schreier, 2018).

The engagement of and benefits for the community sets crowdfunding apart from conventional funding and also indicates an intention that goes beyond consumption needs (Belleflamme et al., 2014; Shneor & Munim, 2019). Correspondingly, platforms serve as transactional intermediaries and to an extent as social networking sites (Colombo et al., 2015; Ordanini et al., 2011). Zhao et al. (2017) support the concept of socializing with the motives of finding likeminded peers and sharing ideas among them. The distinctive step in crowdfunding is however the realization of the idea and constitutes another factor that is argued to motivate investors (Kuppuswamy & Bayus, 2017). In line with traditional motivation theory (e.g. Hull, 1932) and the goal-gradient effect (e.g. Kivetz et al., 2006), the urge to make the difference in reaching the funding target peaks at proximity or when the weight of engagement is at its otherwise highest (Kuppuswamy & Bayus, 2017). Similarly, the explicit focus on the attainment of innovative products can express itself in a sense of responsibility that encourages investors to increase their financial stake (Zvilichovsky et al., 2017). It can also be reflected in a desire to benefit from the innovative good and is discussed in research on user innovation, for instance, which delves into economic inducements as a driver, too (Baldwin et al., 2006; Baldwin & Von Hippel, 2011). Moreover, altruistic sentiments and a desire to help are additional aspects that motivate backers to participate (Kuppuswamy & Bayus, 2017). In general, the motives behind crowdfunding are manifold and can be summarized into intrinsic and extrinsic factors (Cordova et al., 2015).

Fraudulent behavior in the digital space is a matter previously discussed in the context of eWOM but it persists in crowdfunding, as well. User-generated content has been attested to be an object of deceit (e.g. Mayzlin et al., 2014; Luca & Zervas, 2016). In the specific context of crowdfunding, Wessel et al. (2016) revealed that manipulating the Facebook Like count is a problem to be recognized. The authors were surprised to find that faking occurs more often with highly-invested creators that already exhibit higher quality campaigns, which stands in contrast to the findings mentioned for electronic word-of-mouth. Additionally, the authors discovered that occurrence differs by crowdfunding categories since examples like design or technology exhibit higher frequency in illegitimate behavior than art or journalism. Interestingly, Kickstarter removed the Facebook Like count that previously existed on each campaign some time ago, with currently no obvious information regarding the motivation behind it. Nonetheless, the platform still exhibits other forms of information that bear opportunities for manipulation. Examples consist in the advertising of social media, external references, like count on updates and even comments on the crowdfunding campaign, all of which can be argued as a form of electronic word-of-mouth and constitute a subject of investigation. Although this study does not dive into an analysis, these factors are still addressed later on.

On a side note, the pertinence of crowdfunding goes even beyond the scope of its original purpose. Roma et al. (2017) argue, for example, that traditional investors see the amount of contributions a campaign generates as an evaluation criterion (e.g. regarding uncertainty), which affects chances of consecutive financing in a conventional setting, such as venture capital. This is particularly relevant for ambitious undertakings and goes hand in hand with other studies that underline entrepreneur's motives of gaining insights on market potential and idea validation, and the relevance in the field of sustainability (Bento et al., 2019b; Brem et al., 2019). In accordance, crowdfunding has not only been adopted by entrepreneurs in early-staged ventures but also has seen application in enterprises of various sizes and fields (Brown et al., 2017; Wang & Yang, 2019).

2.4 SUSTAINABLE ENTREPRENEURSHIP

Research on sustainable entrepreneurship dates back long before its recent impetus. Its origin is considered in sustainable development, a term that came into existence through the United Nations' (UN) World Commission on Environment and Development (WCED) (alternatively known as the Brundtland Commission) in their publication 'Our Common Future' (also called the Brundtland Report) in 1987 (Anderson, 1998; Crals & Vereeck, 2005). It was rather broadly defined as the intent to satisfy current demands without impairing one's ability to do so in the future (Choi & Gray, 2008; Crals & Vereeck, 2005). However, some research criticizes the lack of specificity as well as unequivocal parameters of measurement and consequently the ambiguous interpretations along with it (Parris & Kates, 2003).

Nevertheless, it did not stop the evolvement of the term sustainable entrepreneurship and its remarkable growth within recent years, especially after the UN's release of the '2030 Development Agenda' in 2015. Terán-Yépez et al. (2020) analyzed the top ten journals within the database Scopus (Elsevier B.V., 2020) that featured the highest output dedicated to the topic between 2002-2018 and emphasize that half of them were founded within the most recent years, namely between 2015-2018; while the first ten years only exhibit about a fifth (21%) of the total articles released compared to a third (33%) in the last year alone. Their data also discloses that respective citations increased by circa 58% in 2015 with further growth after. The correlation with the UN's efforts may give credit to an institutional view in that institutional circumstances affect entrepreneurship and innovation and the acknowledgement within society (Hinings et al., 2018; Li & Zahra, 2012) and blends well with the call for additional research by Liang et al. (2019) who studied crowdfunding backers' motivation to invest with regard to trust.

Various derivatives of sustainable entrepreneurship may specifically focus on combining economic viability with an emphasis on social matters, e.g. social entrepreneurship (Schaltegger & Wagner, 2011), or environmental aspects, e.g. ecopreneurship (Schaltegger, 2002). Yet modern sustainable entrepreneurship is depicted as an integrated approach without prioritizing financial outcome. Instead, it strives for a balance between social and environmental ideals as well as economic feasibility or other private or public gain (e.g. quality of life) regardless of scale (Anderson, 1998; Crals & Vereeck, 2005; Bento et al., 2019b; Choi & Gray, 2008; Shepherd & Patzel, 2011; Terán-Yépez et al., 2020). The three focal points are also referred to as the triple bottom line (TBL) and the aspiration of balancing them is shown to not necessarily happen in idealistic sync but, in practice, in sequential order, too (Belz & Binder, 2017). Sustainable entrepreneurs are portrayed as means of change who lead towards sustainable developments, emphasizing both sustaining and developing separately (Shepherd & Patzel, 2011; Terán-Yépez et al., 2020). Their discernible dedication towards social and environmental progress is also referred to as sustainability orientation (Calic & Mosakowski, 2018). While its core is no longer circling around economic parameters as applicable in classical entrepreneurship, Shepherd and Patzelt (2011) still suggest sustainability as a critical constituent in successful businesses. As a consequence, it hints at sustainability orientation not only being relevant in a niche but also serving as a competitive advantage overall and research into the matter may benefit the economic context at large.

With the ever-growing audience fostered through user-generated content, social themes around the environment or gender and ethnic equality are possibly receiving awareness more than ever. As an analogy to the idiom that a pen may be mightier than a sword, electronic word-of-mouth offers empowerment to voices that may otherwise not be heard. Enabled through its virtually limitless reach, user-generated content thrives throughout different business stages (e.g. idea creation, operations) across borders and cultures (Olanrewaju et al., 2020). It even reaches measurable extent as women in established (Nord et al., 2017) as well as developing countries (Beninger et al., 2016) are seen to capitalize on the possibilities of social media. Although sustainable entrepreneurship research has recently incorporated developing countries as a major study area (Terán-Yépez et al., 2020), it is argued to still be deficient (Olanrewaju et al., 2020).

With the advent of crowdfunding, the empowered voices have received a new level of capacity to organize the desired changes themselves. In terms of gender, conflicting research argues against (Cumming et al., 2019) and for (Barasinska & Schäfer, 2014) overcoming disparities in equity crowdfunding. In a setting of donation-based crowdfunding on Kickstarter, women are particularly successful when choosing industries in which males are disproportionately prevalent, such as technology (>90% male creators), which uncovers an uneven involvement of female investors supporting female creators (Greenberg & Mollick, 2017). Frydrych et al. (2014) also examined Kickstarter campaigns yet focused on the reward-based scheme and their statistical results indicate that circa 69% of projects of female-only founders versus approximately 46% of campaigns of male-only founders were successful. Such findings are observed as especially interesting since the entrepreneurial arena possesses a predominantly male population of founders and investors, who benefit from higher chances in traditional financing. This is also supported by an empirical study concerning reward-based, sustainability campaigns on Kickstarter (Bento et al., 2019b). The authors underline that crowdfunding mitigates barriers of entry and hence lowers impediments for females to gain access to capital. Besides, women are more likely to be part of social campaigns compared to men just like such campaigns are composed of slightly more cross-cultural teams (Parhankangas & Renko, 2017). Thus, sustainable crowdfunding encourages female entrepreneurship as particularly the social rationale holds opportunities for women (Bento et al., 2019b). As a consequence, crowdfunding and eWOM represent effective instruments in dealing with inequality and contribute to addressing and solving social issues. Notwithstanding, literature on female entrepreneurship in general also stresses the impact women render in economic terms or simply in benefits for their community (De Vita et al., 2014).

With reference to topics of climate change, environmental pollution and other areas of environmentalism, sustainable entrepreneurship offers entities unique prospects and facilitates a transition towards a sustainable economy (Crals & Vereeck, 2005). The innovative drive in entrepreneurship is also considered an adequate vehicle for overcoming issues concerning sustainability (Schaltegger & Wagner, 2011). In accordance, its perception has altered in that entrepreneurship is acknowledged as a means of solving environmental dilemmas instead of being considered a source of them (Muñoz & Cohen, 2018). However, conventional investors, such as venture capitalist, are typically less concerned with the public good and the idealistic background that sustainable projects commonly entail but instead focus on metrics that are measurable and profitable, preferably in the short-term (Petruzzelli et al., 2019). At the same time the lack of commercial centrality also constitutes a potential threat with regards to the health of a venture in the long-term (Bento et al., 2019b). Moreover, uncertainties concerning the market or technical feasibility magnify the risk level and deteriorate attractiveness further (Roma et al., 2017). As a consequence, environmental campaigns are faced with additional difficulties compared to commonly commercial projects (Calic & Mosakowski, 2018).

Studies on the credibility of sustainable signals are still very scarce as Wehnert et al. (2019) claimed to be the only one. The authors suggest that the process of certifying sustainable features through an independent third-party would serve as credible signals. According to a study of Crals and Vereeck (2005) however, sustainability certifications are rather complex and resource-intensive and a reason why small- and medium-sized enterprises may not have access to them. Overcoming limitations based on time and financials is one of crowdfunding's strength, though. The collection of funds typically grants the campaign creator a self-declared time window until delivery, as commonly presented in form of a project timeline, and is also denominated as a working capital loan (Belleflamme et al., 2014). Hence, it may allow resource allocation towards acquiring targeted certifications, which creators may use to advertise during the campaign as well as after a campaign, e.g. in form of updates, when seeking ongoing funding.

The landscape of entrepreneurship and its access to financial means has been democratized since the inception of crowdfunding (Shneor & Munim, 2019). The discrepancies between traditional investors and those in crowdfunding may thus serve as an opportunity in this regard. This can be exemplified by consumers' altruistic motives as well as their drive to innovate and are present in, both, eWOM and crowdfunding literature, as previously discussed. Particularly intrinsic motivations can hence be of relevance concerning the topic of environmentalism. Furthermore, Bento et al. (2019b) provide a rare insight and claim that an average of 70% of the sampled reward-based, sustainability projects on Kickstarter that succeeded funding remain operational a year after campaign end. The authors thereby confirm the appropriateness of this instrument of entrepreneurial finance in this context of sustainability and describe it as a creative method of resolution. Nevertheless, crowdfunding's role in sustainability is a subject that has yet to be extensively explored since literature is comparably scarce, particularly empirically, and its comprehension is still lacking (Bento et al., 2019b; Petruzzelli et al., 2019).

3. THEORETICAL FRAMEWORK

With the groundwork of literature on the topics being laid out, this consecutive chapter details the theoretical background and establishes the hypotheses of the research. The section ends by portraying a research model in a visual representation to facilitate comprehension and reproducibility.

3.1 SIGNALING

The theory of signaling (Ross, 1977; Spence, 1973) has gained attention in academic literature since its foundation in the 1970s and exhibits notable occurrences in the fields of electronic word-of-mouth (e.g. Cheung et al., 2014) and crowdfunding (e.g. Ahlers et al., 2015). It is based on information economics and addresses information asymmetry and its consequences (Biswas & Biswas, 2004). In a common market situation, the parties involved in a transaction do typically not possess an equal amount of information over the subject (Kirmani & Rao, 2000). Still, in a traditional setting customers may manage the disadvantage over the salesperson with the help of an amplitude of physical signals regarding the product itself, the seller and the environment. However, physical characteristics vanish at latest with a shift towards the online realm, which is apparent in the context of e-commerce. In the early days, online transactions were exclusively limited to a one-sided control over which information are made available (Wessel et al., 2016). The computer-mediated nature hinders customers to scrutinize indicators of quality, which would otherwise be possible with physical experience (Pavlou et al., 2007). Thus, the flow of information is in the hand of the business and causes asymmetry, uncertainty and risk for consumers (Pavlou et al., 2007; Wessel et al., 2016).

Discrepancies in the availability of information among parties may have drastic implications as they affect the connection between customer and seller as well as the transaction itself (Kirmani & Rao, 2000). The consequences may come in form of inefficiencies in communication, customers' prioritization of prices over unascertainable quality, or may even end in market failure (Akerlof, 1970). Due to the extent of the dilemma, the topic is considered throughout organizational activities such as finance, marketing and human resources (Kirmani & Rao, 2000) – and thence to an extent to crowdfunding. Human resources are actually an early academic example of signaling theory when Spence (1973) explained it addressing the difficulties of assessing employees' abilities. In order to overcome information asymmetry, a party may draw on inferences of quality (Ross, 1977; Spence, 1973). Examples in consumer markets consist in marketing, pricing, reputation, warranty and refund assurance and aim to make quality more observable (Biswas & Biswas, 2004; Kirmani & Rao, 2000). Therefore, these often refer to information about the seller, who is able to utilize signals strategically, which also hints at the potential to manipulate them to gain advantage (Mavlanova et al., 2012; Wessel et al., 2016). With regards to the process of sending and receiving signals, one may hence adumbrate that information economics in form of signaling appears, in a simplistic view, similar to the previously discussed domain of social communication and thereby word-of-mouth (see section 2.2).

In general, research argues for consumers to rely more on some signals in an online setting compared to physical experiences in stores (Biswas & Biswas, 2004; Mavlanova et al., 2012). This is in line with the notion that asymmetrical information and uncertainties are more pronounced in an online environment, also because the product is physically assessable only after the purchase and the limited signals that are available are therewith gaining in importance (Biswas & Biswas, 2004; Mavlanova et al., 2012; Wessel et al., 2016). Reward-based crowdfunding further deepens this gap by having substantially longer times of delivery and a lack of binding assurances that the good may be provided at the advertised quality or even at all (Mollick, 2014; Wang et al., 2017). Thus, to some degree the offers in reward-based crowdfunding can be compared to experience goods, which, according to Nelson (1970), are those that exhibit higher uncertainties and asymmetrical information since they cannot be properly evaluated until receipt and consumption (Wessel et al., 2016). Also, the search cost for the purchase decision-making are declared to be higher (Park & Lee, 2009).

The issue intensifies distinctly in the context of sustainability. Wehnert et al. (2019) argue beyond the categorization into experience goods and reason that social and ecological factors are rather impossible for a consumer to verify without the help of independent third-parties. Hence, the authors classify attributes of sustainability to be of credence, which consequently restricts credibility considerably. When ignoring the characteristics of a crowdfunding setting, technology products could be designated as search goods since their features could be objectively appraised to some extent as long as the information is properly disclosed (Bi et al., 2017; Nelson, 1970). However, technology products can be considered complex, which can be attributed to a large number of features and layers (Scholz et al., 2010), and therefore they posit effortful assessment of credible data, which is reinforced by the uncertainties that crowdfunding entails (Choudhurry & Karahanna, 2008; Wehnert et al., 2019).

A common behavior for market participants to cope with uncertainties consists in herding (Zaggl & Block, 2019). According to Banerjee (1992), herding affects the decision-making process through imitation in cases of asymmetrical information. Actions of others are followed as they are perceived to possess superior knowledge and represent a signal of unobservable information (Banerjee, 1992). In reward-based crowdfunding, Colombo et al. (2015) discover that herding during early contributions are indeed positively related to campaign performance. Zaggl and Block (2019) extend the knowledge by finding positive effects only when backers' pledges are high enough and describe it as a paradoxical dilemma since crowdfunding fundamentally relies on smaller financial contributions. Yet Zvilichovsky et al. (2017) note that herding thrives on backers' drive to realize the commercialization of an innovative product campaign, which may negate a potential threat of low investment amounts in early contributions.

With reference to typically lower barriers of entry in crowdfunding (Bento et al., 2019b) along with the fact that investors have mostly lower expertise and fewer resources available to evaluate a project (Ahlers et al., 2015), the identification of quality campaigns constitutes an intricacy that may be difficult to resolve (Wang et al., 2017). On the side of the sender (i.e. creator) it is to be noted that the challenge consists in the credibility of the signals in order for them to be effective (Courtney et al., 2016; Wang et al., 2017). This may involve delegating the task to a third-party (Courtney et al., 2016) and can be argued to include consumers as previously elaborated in the literature review about eWOM (see section 2.2). Indeed, it is already evident in the research domain of electronic-word-of-mouth, which concludes that the impact of messages varies depending on the individual receiving it (Cheung & Thadani, 2012) as well as due to discrepancies among and even within the same channel of communication (King et al., 2014). An investigation into which signals matter can therefore be complemented with a theoretical base involving the persuasion of information, such as the Elaboration Likelihood Model.

3.2 ELABORATION LIKELIHOOD MODEL (ELM)

The dual-process theory exhibits a notably long history in research. Relevant literature goes back decades and comprises prominent examples of Deutsch and Gerard (1955) as well as Evans (1984). The theory distinguishes between two distinctive ways of evaluating information. As defined by Deutsch and Gerard (1955), informational influence reflects the effect that is present when a receiver of information internalizes these as valid. This is related to what Evans (1984) adapted into a cognitive approach of processing, which the author labels as analytical. Normative influence, on the other hand, is delineated as the conformance to expectations out of either abiding (i.e. utilitarian) or identifying (i.e. value-expressive) purposes (Deutsch & Gerard, 1955; Racherla & Friske, 2012). Drawing inferences on affective cues is related to the heuristic reasoning adapted by Evans (1984).

Based on this two-fold character, Petty and Cacioppo (1983, 1986) popularized the Elaboration Likelihood Model that has become an acknowledged theory in the study of behavioral or attitudinal change through exposure of an influential stimulus (Cheung & Thadani, 2012). In other words, ELM provides a theoretical lens with which the act of persuasion can be analyzed (Allison et al., 2017). ELM distinguishes the influence based on the dual-process theory and labels it to be either central or peripheral (Petty & Cacioppo, 1983). Analytical assessment occurs in the central route, which deals with information that is essential to the subject and of primary relevance (Petty & Cacioppo, 1986). The processing of the stimulus is done through critical evaluation and thus demands cognitive efforts (Allison et al., 2017). The peripheral route, on the other hand, concerns contextual aspects around the subject and does not include the appraisal of the content itself (Petty & Cacioppo, 1986). Hence, a receiver processes the stimulus without much thought (Bi et al., 2017).

An essential aspect when reacting to stimuli is considered to be the extent of elaboration on the receiving side (Cheung & Thadani, 2012). With reference to its theory, elaboration is described as an active process in which the audience puts their own thoughts forward to evaluate the message (Petty & Cacioppo, 1986). The degree of elaboration thus hints at whether an individual is rather influenced by the central (high elaboration likelihood) or peripheral (low elaboration likelihood) route and the moderation into either is dependent on the processor's motivation and ability (Lou et al., 2014; Wang & Yang, 2019). Cheung and Thadani (2012) state that the moderating variables either reflect how relevant (i.e. motivation) the topic is to the audience or how knowledgeable (i.e. ability) the individual is on it. However, Allison et al. (2017) stress that the moderation is not exclusive to each other in that one route would cease to matter entirely. Additionally, the authors generally presume that the occurrence of either approach of processing, be it by adhering to the central or peripheral route, would not necessarily end in diverging effects. Said differently, consumers may conclude the same decision regardless of which route weighs the most. Considering the diversity of consumer backgrounds (Kraus et al., 2016) it is however still relevant to know which factor is the most influential and thereby knowing which lever potentially boosts participation. Hence, the Elaboration Likelihood Model seems to complement the theory of signaling well with its additional insights into the decision-making.

As mentioned, the Elaboration Likelihood Model is relevant in both, eWOM as well as crowdfunding, scenarios. In fact, the dual-process lens is argued to be a dominant theory within research into electronic word-of-mouth (Cheung & Thadani, 2012). In the field of crowdfunding, ELM is pertinent with reference to consumers' purchase decision-making (Allison et al., 2017). As previously discussed, reward-based crowdfunding represents a form of pre-market in which investors are typically able to pre-order goods (Belleflamme et al., 2014; Bento et al., 2019b). On that note, Wang and Yang (2019) argue the campaign page to be an advertisement that constitutes of information intended to persuade consumers to invest, which naturally implies that the process of decision-making involves a certain amount of evaluation. In accordance, engaging in reward-based crowdfunding can be viewed as an act of consumer purchase decision-making (Beaulieu et al., 2015; Liang et al., 2014). Thence, literature indicates the appropriateness of ELM in reward-based crowdfunding (Allison et al., 2017; Bi et al., 2017; Liang et al., 2014; Wang & Yang, 2019).

3.3 HYPOTHESES

The investigation of persuasive signals in reward-based crowdfunding through the lens of ELM has been addressed in very few studies, which include Allison et al. (2017), Bi et al. (2017), Liang et al. (2019) and Wang and Yang (2019). In line with the theory provided by Petty and Cacioppo (1986), the four studies incorporate central and peripheral factors and, with the exception of Bi et al. (2017), consider moderators. The four papers determine critical information regarding the project's quality to frame the central route. Since these factors are arguably of primary relevance to a potential backer (e.g. Petruzzelli et al., 2019), it is reasoned to be consistent with the explained theory. Synthesizing the papers, the central route may then be divided into elements about the offer as well as the creator.

With respect to cues about the product itself, Liang et al. (2019) show positive results in their hypothesis concerning accurate and complete information. A more common and specific construct is found in descriptive elaborateness and has also been a prominent subject of interest in eWOM research, too (e.g. Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010). With regards to crowdfunding, the comprehensiveness of a campaign stands for more detailed information, which in turn adheres to the logic of Brynjolfsson and Smith (2000), who claim that more information helps consumers reduce informational disadvantage and uncertainties. This may be particularly applicable to technology products (Bi et al., 2017) since their specifications are more straightforward to search and compare – see section 3.1. Empirical results in reward-based crowdfunding confirm the positive impact of descriptive elaborateness' on campaign performance and are exemplified by the studies of Bi et al. (2017) and Kim et al. (2017). Lagazio and Querci (2018) also concur and discovered that investments in non-hedonic goods are more susceptible to extensive written information compared to a video.

An audiovisual pitch on the campaign page is however an iconic feature on Kickstarter, which even pointed out itself that a lack thereof equals recognizable detriment (Bi et al., 2017). According to Mollick (2014) and Wang et al. (2017), the integration of an introductory video is considered to signal preparedness to potential backers, who thus may perceive the additional efforts of the creator in preparing more descriptive written and audiovisual content as indicators of quality. This notion is endorsed through a multitude of crowdfunding literature such as Bretschneider and Leimeister (2017), Kraus et al. (2016), Parhankangas and Renko (2017), Wessel et al. (2016). Mollick (2014) discloses lower probability of funding by 26% in absence of a video and therefore confirms its relevance empirically. On the other hand, Lagazio and Querci (2018) document a negative relationship, namely five percent lower success chances independent of descriptive elaborateness. The research of Bento et al. (2019b) yet again finds a positive relationship even for sustainability projects – with a p-value of 0.01. Hence, the more dominant opinion is followed in that videos positively influence backers in their decision to invest. As a consequence, indicators regarding to the quality of the offering are hypothesized as:

H1a: Higher descriptive elaborateness relates positively to funding intention.

H1b: Audiovisual cues in form of a video relate positively to funding intention.

Besides inferences about the quality of the pitched crowdfunding product, investors may also be interested in the personnel that is involved and responsible of fulfilling the promises made. Entrepreneurs that present insights about their abilities are said to influence investors' trust and thereby their intent to invest (Liang et al., 2019). In accordance, Ahlers et al. (2015) found positive impact on crowdfunding performance among creators with an MBA degree. However, Allison et al. (2017) found partially negative effects of education. These results did not hold in additional testing as well as a second experiment though and instead resulted in a change towards a positive and significant influence. Overall, the competence of an entrepreneur is stressed to be a valuable signal for the quality of the product advertised and is also supported empirically (Wang & Yang, 2019). The expertise of creators may not only be represented by their educational achievements but also by their professional background. Prior campaign experiences can be an example of it and Mollick (2014) suggests that entrepreneurs with more experience appear more qualified to succeed. Zhou et al. (2016) underline the relevance of previous experience in their exploratory study. This is also confirmed by Kim et al. (2017), who focused their study on project- and creator characteristics. They suggest a positive relationship with campaign success and depict empirical support for it. Thus, the hypotheses regarding the background of the project creator are as follows:

H2a: Higher entrepreneur's education relates positively to funding intention.

H2b: Higher entrepreneur's experience relates positively to funding intention.

In the domain of electronic word-of-mouth, literature has often distinguished indications of product quality to constitute the central route whereas matters of eWOM have been categorized as peripheral cues that influence decision-making (Gupta & Harris, 2010; Park & Kim, 2008). With the issue-relevant cues being addressed in the hypotheses above, the next introduce eWOM as contextual information. The paper of Bi et al. (2017) is of extraordinary relevance in this context because it is the only one to apply the theories of ELM and signaling in a research addressing electronic word-of-mouth in crowdfunding and adheres to the division above. With reference to the discussed Elaboration Likelihood Model, affective cues involve contextual factors that are less intensive for the audience to process (Petty & Cacioppo, 1986) - and the pertinence of eWOM in sustainability crowdfunding regarding its potential heuristic benefits are not unheard of (Wehnert et al., 2019). Thus, it appears reasonable to reduce electronic word-of-mouth to a quantitative dimension. Disregarding a qualitative analysis of eWOM is also a logical constraint of this research because literature has provided a vast amount of criteria to consider (e.g. Cheung & Thadani, 2012; King et al., 2014) yet resources to pursue this study are limited. Nonetheless, this approach is not unique and seen in other studies in crowdfunding such as Bi et al. (2017) and Wessel et al. (2016). Both papers utilize the Facebook 'Like' button as a quantitative measure of social buzz, for instance. However, this feature is no longer present on Kickstarter and hence alternatives have to be derived.

The element of community is a strong characteristic in crowdfunding and eWOM alike (cf. Belleflamme et al., 2014; De Valck et al., 2009). The creator's connections on social networking sites are argued as an initial group of people to reach (Wessel et al., 2016). The reliance on participants is a critical premise of crowdfunding (Wang & Yang, 2019) and hence social media is highly relevant for consumers to connect in this context (Olanrewaju et al., 2020). Consequently, metrics regarding social media are crucial for crowdfunding (Olanrewaju et al., 2020) and represent an instrument of audience growth (Lagazio & Querci, 2018). Shneor and Munim (2019) suggest social information to even be essentially embedded in the crowdfunding act. The crowdfunding process is said to comprise the interactivity of social networking sites and the exposure of eWOM, which helps resolving the dilemma of asymmetrical information and is thus argued as a vital signal in backers' decision-making (Manes & Tchetchik, 2018; Shneor & Munim, 2019; Wessel et al., 2016). This is complemented by a look into sustainability dynamics from Wehnert et al (2019), who argue that the informational disadvantage requires backers to draw inferences from additional signals of quality (cf. Kirmani & Rao, 2000).

In fact, the exchange of information in the context of crowdfunding is empirically confirmed to influence the funding behavior and the otherwise neglected duality in material (i.e. investment) and immaterial (i.e. eWOM) contribution is emphasized (Shneor & Munim, 2019). Further, metrics such as the amount of shares (Lagazio & Querci, 2018) and network size (Mollick, 2014; Yang & Berger, 2017) constitute a driving force in interconnecting crowdfunding and social media (Olanrewaju et al., 2020). As a consequence, the advertisement of social networking platforms on the campaign page may contribute to its performance. Furthermore, Bi et al. (2017) discover third-party information about the offering as a very significant ($p<0.001$), positive influence on the funding intention and underline that references in the form of eWOM serve indeed as impactful cues. Lastly on this topic, the engagement in exchange is also found to contribute to project performance in case of a joint forum (Kromidha & Robson, 2016) as well as the campaign's comments section (Cho & Kim, 2017; Courtney et al, 2016; Kim et al., 2017; Wang et al.,2017). Therefore, eWOM is hypothesized to affect the decision to invest as follows:

H3a: Comments on a campaign page relate positively to funding intention.

H3b: Advertising of social platforms relates positively to funding intention.

H3c: References on a campaign page relate positively to funding intention.

With reference to the triple bottom line of sustainable entrepreneurship, namely social, environmental and economic aspects, the weight of the motivations that drive crowdfunding participation may shift (Bento et al., 2019b). In other words, moral concerns may initiate investors to participate more strongly than for conventional ideas. Since Kuppuswamy and Bayus (2017) describe pro-social motives to be among the reasons for the overall engagement in crowdfunding, it gives credit to incorporate such affective element – particularly in the case of a peripheral cue. Literature in the domain of crowdfunding has started to take notice and Calic and Mosakowski (2016) showcase empirical results for sustainable-oriented campaigns. In their paper, the authors investigate social and environmental aspects of reward-based projects on Kickstarter and find those to positively impact campaign performance in the category of technology products. As a consequence, the following hypothesis is deduced:

H4: Sustainability orientation relates positively to funding intention.

When it comes to evaluating indications of quality, the Elaboration Likelihood Model assumes individuals to either follow the central or peripheral route (Petty & Cacioppo, 1986). The degree of elaboration is said to depend on the ability and motivation of a processor (Lou et al., 2014; Wang & Yang, 2019). In the domain of electronic word-of-mouth, research commonly translates these into how knowledgeable the audience is, or the extent of relevance and personal involvement regarding the topic (Cheung & Thadani, 2012).

In crowdfunding, papers relate the involvement of the individual to the core premise of the crowdfunding act: financials (Allison et al., 2017; Liang et al., 2019). Rewards are offered at various prices among and within projects. It is argued that the consequences of participation increase with higher amounts of investments (Liang et al., 2019) as well as less competitive pricing compared to the larger market (Allison et al., 2017). Considering the uncertainties that reward-based crowdfunding entails (Mollick, 2014), the decision to participate in a campaign may then imply the financial risk in either losing one's money in case of non-delivery or not getting one's money worth in case of insufficient quality. Therefore, the financial requirements represent a campaign characteristic that may motivate backers to allocate more or less of their cognitive capacity to the appraisal of the offer (Allison et al., 2017; Liang et al., 2019). Thus, the moderation through motivation is hypothesized as such:

H5a: Low financial involvement increases the influence of the peripheral route on funding intention.

H5b: High financial involvement increases the influence of the central route on funding intention.

Next to moderation through campaign characteristics, also the investors exhibit attributes that may affect which route of processing weighs most. In studies concerning electronic word-of-mouth it is commonly perceived that the audience chooses between analytical efforts (i.e. reviewing the issue-related content) and affective behavior (i.e. contextual factors) based on their knowledge of the subject (Cheung & Thadani, 2012). Similarly, Wang and Yang (2019) reason that the ability of backers to adequately appraise an offer can be expressed by their level of understanding of the topic. The authors argue that knowledge is of particular relevance in crowdfunding because of its innovative and pre-market character. Their empirical results confirm a positive relationship to the intention to invest at $p < 0.01$. In spite of the original considerations for a questionnaire, this paper utilizes data available from the platform itself. Consequently, backers are not able to give personalized insights. Instead, the estimation of backers' ability is inferenced by the only available alternative: experience. This approach is also present in the paper from Allison et al. (2017), who argue that recurring backers gain expertise that are relevant in the context by accumulating experience. Said differently, consumers that are new to crowdfunding may then depend more on peripheral cues since their knowledge is not sufficient for proper analysis. However, the empirical results by Allison et al. (2017) only partially confirm this notion. Still, Shneor and Munim (2019) construe in their study that recurring backers are more likely to invest higher amounts, which in itself is not probative but perhaps indicative. Therefore, backers' ability is hypothesized to influence as follows:

H6a: Low backer experience increases the influence of the peripheral route on funding intention.

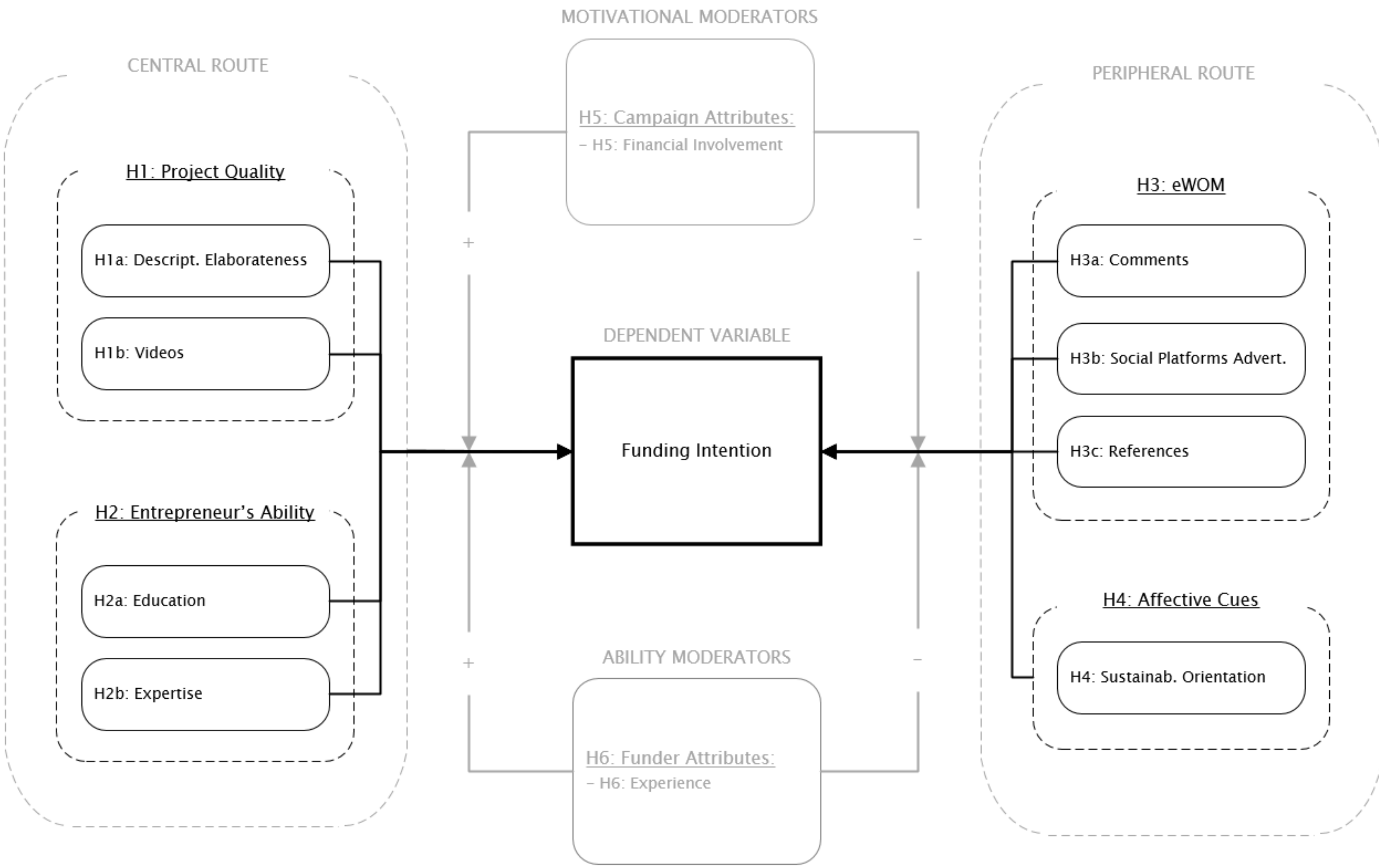
H6b: High backer experience increases the influence of the central route on funding intention.

3.4 RESEARCH MODEL

In order to alleviate the comprehension of the hypotheses, the research is illustrated in the graphic below (Figure 1). Its inspiration is derived from the previous work of Allison et al. (2017). The paper of Bi et al. (2017) acts especially as referee for integrating electronic word-of-mouth. Additional papers of Liang et al. (2019) and Wang and Yang (2019) adumbrate overall support considering the extent of resemblance. In line with literature, the research model visually separates the central and peripheral route from each other and symbolically encloses the respective variables. The center of attention, namely the dependent variable, is visually positioned accordingly. Moderators are displayed in a way to allow the emphasis of interaction. Altogether, the research model acts as a visualized summary of the hypotheses deduced.

Figure 1

Research model



4. METHODOLOGY

A common denominator for academic research builds upon the framework popularized by King et al. (1994). The authors argue quantitative and qualitative research to be of complementary nature and address common guidelines for proper research design. With reference to their suggested four elements, this chapter closes the theoretical phase by explaining how the empirical part is conducted along with the variables themselves. It is also in line with Creswell's (2003) three essential points of research design as this chapter follows upon the previously made theoretical claims with the strategy of aggregating data and the method of processing it.

4.1 APPROACH

In part, scientific research bases its strength on drawing inferences from empiric observations with the help of statistics, such as in the form of descriptive or explanatory terms (King et al., 1994). As a consequence, academic studies may involve sampling from a dedicated population. The sample is to be inspected regarding its characteristics, hypotheses are to be tested and generalizations may be concluded regarding the population at large. Often, models are constructed to guide this process. Models serve as a simplified representation of reality within the problem domain considered and are validated or falsified through statistics about the data assembled, which thereby appraise the parameters of the population. Extracting subsets from a larger base enables researchers to greatly reduce the resources required to accrue, process and interpret the data or even facilitate feasibility at all.

However, a sample is not a perfect reflection of the population per se. In fact, a sampling distribution model (also known as probability model) specifies the issue of differences in proportions throughout multiple samples of identical size within the same population. For a sample to be considered an adequate representation of the population, the normal distribution presumes criteria to be met. An important requisite for normally distributed data lies in the randomization approach. The condition implies that all observations in the sample are based on equal chance and not determined by proactive choice. Benefits of randomization include higher internal (e.g. countering confounding variables) and external (e.g. more attributes of a population represented) validity. Unfortunately, the exertion of simple random sampling is an ideal that is not always feasible in practice as is the case with this study. Without random assignment, unobserved variables may posit threats of confounding and therefore endogeneity (Wang et al., 2018). One way of mitigating the problem in this study, however, is done through an excessive collection of control variables. Whereas the research model (Figure 1) states ten variables to be incorporated into statistical analysis, a total of 93 variables are gathered, of which a respectable number actually receives statistical attention. Nonetheless, non-probability sampling exhibits implications that need to be considered and poses restrictions on this research. On the upside, efficiency in resources and approachability are advantages that matter especially for a study like this. Data can be accessed, stored and used immediately as to be explained in the next subchapter. However, non-probability sampling typically cannot satisfy standards of reproducibility, representativeness and bias. Especially the extent to which a sample is representative of the group at large is difficult without definite knowledge about the population Due to limited resources in this study it remains a restriction, indeed. Yet again, actions are taken to normalize the process to at least reduce some adverse effects, as to be discussed later, as well.

In order to reach rather definitive findings, experimental studies offer superior traits in the comprehension of causal relationships. Causes and effects are more adequately investigated with the help of control groups and the ability to manipulate a treatment in a controllable manner. A truly experimental design in line with scientific requirements features both qualities in addition to randomization to reckon causality. However, proper experimental studies also exhibit disadvantages. These include not necessarily being free from bias or artificial or ethical dilemmas either, as well as potentially requiring a lab-like environment and being obtrusive and resource-intensive. Unsurprisingly, this study faces evident restrictions in this regard and therefore follows a non-experimental design. As a consequence, data is collected as natural observations, i.e. as is, without the possibility to manipulate and, in turn, without proper basis for causality. Thus, discrepancies between groups cannot be allocated to independent variables but only analyzed with reference to the predicted variable. An alternative approach to analyzing causal relationships consists in prediction techniques. Regression is a prevalent statistical approach for a predictive model. Its ascendancy is visible across both research areas of eWOM (e.g. Cheung et al., 2014; Chevalier & Mayzlin, 2006; Manes & Tchetchik, 2018; Mudambi & Schuff, 2010; Racherla & Friske, 2012; Smith et al., 2012; Yin et al., 2016; Yoo et al., 2013; Zhu & Yang, 2010) and crowdfunding (e.g. Ahlers et al., 2015; Allison et al., 2017; Cho & Kim, 2017; Kim et al., 2017; Lagazio & Querci, 2018; Mollick, 2014; Nucciarelli et al., 2017; Parhankangas & Renko, 2017; Roma et al., 2017; Shneor & Munim, 2019) and even found in the niche of sustainable crowdfunding (e.g. Bento et al., 2019a, 2019b; Calic & Mosakowski, 2016; Chan et al., 2020; Hoerisch, 2015). Although regression appears to imply causality in its approach, it is only a statistical tool which results may have predictive power. It does not serve as evidence of causal relationships. This is a boundary that a non-experimental design cannot overcome regardless of how sophisticated the quantitative approach applied is.

Regression formulates the intercept (y-axis) on the left side and the slope (x-axis) on the right side of the equation. Often, a line of best fit is sought via ordinary least squares (OLS) with the aim to reduce the sum of squared differences. This paper follows suit. The coefficients of the equation describe the relationship between the dependent (DV) and independent variable(s) (IV).

A strength of regression consists in its flexibility. Regression analyses are able to include either single or multiple variables on both sides of the equation. Its modelling may vary from linear over curvilinear (with polynomial terms) up to non-linear relationships, enumerated in order of typical complexity. Accordingly, regression allows analyses of different relationships. It also includes the option to test for interaction effects, which is relevant for the moderation hypotheses present in this study. Notwithstanding, an essential feature of regression that facilitates its predictive power comprises its ability of controlling. Regression can statistically estimate the effects of each independent variable by mathematically manipulating each one. This occurs while keeping all other variables approximately the same. On that account, regression unravels the predictive strength of individual variables. More concretely, the calculated coefficients of the equation allow predicting the change in the dependent variable by a change of one unit in the independent variable(s) as long as transformations (e.g. logarithmic) and scaling are considered.

Linear regression is a common type that is applied throughout research on eWOM (e.g. Dhar & Chang, 2009; Dou et al., 2012; Khan, 2017; Lis, 2013; Luo et al., 2014) as well as crowdfunding (e.g. Burtch et al., 2013; Cordova et al., 2015; Wang & Yang, 2019; Zaggl & Block, 2019). Whereas the dependent variables are required to be continuous in nature, the independent variables are allowed to feature a metric or categorical measurement. Categorical variables either disregard (i.e. nominal) or consider (i.e. ordinal) a specific order but both do not exhibit a determined unit of measurement. Metric variables on the other hand are defined in their measurement unit but differ in whether the value of zero holds any meaning (i.e. ratio) or not (i.e. interval). The most straightforward form of regression is simple linear regression. This method models the dependent variable (also known as response or predicted variable or regressand) against a single independent variable (also called explanatory or predictor variable or regressor). A required complexity level upward is made through multiple linear regression. Albeit this study only focuses on one response variable to determine funding intention, multiple linear regression also allows for multivariate models, which means that more than a single DV can be investigated simultaneously. Its relevance lies in the fact that the same holds true for the side of the predictors. As a consequence, regression can be applied with several independent variables in the equation. Since linear regression can even integrate both measurement levels of independent variables within the same model, it thus is an adequate technique for this study. Due to this, it allows variables with different levels of informational richness to be analyzed together.

As a whole, the research model (see Figure 1) displays multiple independent variables. The total impact of all ten predictors tested together exhibits shortcomings that hierarchical regression may be able to mitigate, following Anderson's (1986) work on hierarchical moderated regression. The Dual-Process Theory perceives two routes of processing with overarching moderating variables that cause the preference of either route. Accordingly, steps are subjoined to the regression in which variables are added or removed from the model tested in order to distinguish differences among the variables and their combinations. Doing so, interpretations are possible with regards to each route's own influence (i.e. central vs. peripheral), the impact of each moderator (i.e. financial motivation vs. backers' experience), interaction terms of IVs with the respective moderators and the inclusion of control variables. Hierarchical regression also enables researchers to investigate which variables are the most significant and contribute the most to the model. Thereby the model can be reduced in its number of variables to conclude with the simplest model of statistically significant variables and avoid overfitting the model to artificially increase R-Squared by the addition of irrelevant regressors. R-Squared Adjusted and the F-value are terms that matter in this process particularly. R-Squared does not decrease in value regardless of which variables are added. Yet the same does not apply for the alternatives. These terms test for statistical significance to consider the actual predictive contribution of a variable instead of including predictions based on chance. The exclusion of independent variables comes at the risk of overlooking mutual association, though. Therefore, such undertaking is advised to take a conservative approach. Nevertheless, without the extension of the additional steps in the regression the researcher is under higher pressure to precisely specify the model in advance and is fairly limited in the ability to inspect the differences between the variables and hence also regarding the fit of the model. This study uses hierarchical regression accordingly.

Before tapping into the manual procedure of adjusting the amount of regressors within the model, computer software facilitates researchers to test a larger set of variables by distinguishing the most relevant variables with the help of algorithms. One technique is known as stepwise regression and typically helps unravel which variables a researcher should pay attention to, especially in earlier phases of research. Although this paper is past such point, stepwise regression still offers benefits to this study. It can be helpful in determining the relevance of control variables, which in this study consists in a substantial part of the 93 variables amassed per campaign. Testing all variables manually in an even bigger number of variations is an unreasonable task within the scope of this research. It still is partly executed for testing and validation purposes in a trial and error approach, nonetheless. Yet, software plays a crucial role in approving the designated research model. Moreover, stepwise is alike hierarchical regression in so far that both are approaches that allow calculating which variables are the strongest predictors through a step-by-step process. As mentioned, stepwise regression does this automatically on the basis of statistical significance of each variable and follows either a forward or backward approach. The former (i.e. forward) starts with the statistically most significant variable and adds only the next most significant after. The latter (i.e. backwards) starts with all defined variables and then deletes the one with the least predictive strength in iterations. Both approaches are utilized in this study to more confidently state a consensus. A downside of the algorithm used within stepwise regression is found in its limitation to not fit all models imaginable but instead concluding with a single model that is strong but not all-encompassing and definite. Hence, stepwise regression is a valuable tool, which on the other hand does not make the manual approach of hierarchical regression obsolete.

The execution of statistical analysis requires awareness of a multitude of rules. Referring back to the criterion of normal distribution, randomization is an ideal way of approaching such. Simple random sampling is not the exclusive method, though. The Central Limit Theorem (CLT) argues that the larger the sample size the higher the convergence towards normality within the probability model of the sample's mean. CLT claims this to be true regardless of the distribution of population from which the sample is taken, though it does presuppose that the observations are independent. Since independence and a preference for larger sample sizes are further criteria which are requisite for normal distribution, the CLT complements the assumptions well. Another factor to consider before assuming normality concerns the skewness of the data and hence researchers need to pay attention to outliers. Next to fundamental assumptions in statistics there are some that are specific to linear regression. Most of the additional conditions relevant to linear regression are assessed through an inspection of the regression's residuals.

Residuals are the remainder of the sample's data that the researchers' model cannot explain, in short: observed minus predicted values. The least squares regression line, also known as the line of best fit, estimates an outcome of each data point in the regression. Visualizing the residuals can be achieved through plotting the observed versus the estimated values. The residuals then become visible as the vertical distance between the observations and the fitted line. Positive residuals relate to the observations that are above the regression line and negative residuals belong to the observed values below. The sum of the residuals as well as their mean equals zero. Yet, the average distance of values that are off the line of best fit is titled the standard error of the estimate or regression or slope and is calculated by taking the square root of the squared average of these distances. This term posits an alternative to R-Squared when it comes to judging how well the researchers' model matches the data. The advantage of the standard error in examining the model's fit comprises of its insight into how precise the predicted values are.

As previously discussed, the predicted variables (y-axis) are placed on the left side of the regression equation and the predictors (x-axis) are located on the right side of it. Next to the IVs, also the constant and the error term are appended. The deterministic power of a regression ideally consists in the variation that the independent variables along with the constant are able to explain. On the other hand, the error term (i.e. residuals) represents the stochastic part of the equation and is supposed to be random. Residuals should not enable systematic prediction of values. Correspondingly, random scatter should be visible when graphically illustrating the residuals in a scatterplot. When true, the assumption of independence is supported. A deeper look into the correlation of the residuals is especially useful in studies that include time-series data. The Durbin-Watson test statistic (Durbin & Watson, 1951) is a technique with which autocorrelation could be investigated. In addition, if the errors are constant across all predictors, then the regression achieves perfect homoscedasticity among the residuals and thereby fulfills another assumption. Homoscedasticity also matters with respect to OLS because ordinary least squares regression presumes equal variance throughout the population. It also extends to the analysis of variance (ANOVA), which is part of a regression analysis. An ANOVA applies the F-Test by dividing the mean sum of squares between groups by the one within groups and implies constant variance among them. However, commonly the assessment of homoscedasticity is not entirely strict and the violation of the assumption rather increases in importance by shifting towards more obvious heteroscedasticity. Once again, the visual approach helps identifying any patterns in the residual scatter. A classic example of heteroscedasticity is a cone-shaped distribution of residuals that is easy to spot in a scatterplot of the residuals since its spread changes over every value of x. The issue with heteroscedasticity lies in OLS's inability to deal with the increased variance and hence may cause an overestimation of statistical significance, viz. falsely lower p-values.

Furthermore, the general assumption of normality is also applicable to linear regression as well as the included ANOVA, albeit primarily with regards to the residuals for the former. Normally distributed data strengthens the reliability of the regression's statistical output and the condition is satisfied when the histogram of the residuals roughly follows the typical bell-shape or when the residuals don't fall off far from the line of a normal probability plot. Alternatively, the presence of normal distribution can be checked via the Kolmogorov-Smirnov test, for example. In a simplified explanation, this non-parametric technique calculates the portion of the data below or above the normal curve and allows decision-making based on common significance testing. Normally distributed and homoscedastic data negates the need for strict linearity, which otherwise is another presupposition in linear regression. On that note, the regression equation implies a linear relationship between the variables of the model. Linearity of the functional form can be examined through scatterplots of the dependent versus independent variables or their correlation coefficient 'R'. The correlation between variables also matters in terms of multicollinearity. As explained, one of regression's strength is its ability to statistically estimate the effect of one variable while keeping the others approximately the same. Intercorrelation between predictors impedes this endeavor because the manipulation of one variable may impact the intercorrelated variable, too. Such relation can be distinguished as structural or data-related. Structural multicollinearity needs to be considered within this research due to the consideration of moderators and respective interaction variables that are created for the model. On the other hand, data multicollinearity is not self-created but a natural characteristic of the sampled data. Although multicollinearity bears no impact on the precision of the model, its presence may distort the statistical significance as well as the coefficients of the variables. Variance inflation factor (VIF) is used to evaluate the level of multicollinearity and Pearson's correlation coefficients give additional insight into pairwise collinearity.

Conclusions based on hypothesis testing are prone to mistakes. The null-hypothesis represents an association with the opposite of the theory tested. Rejection of it depends on a previously set significance level, commonly known as 'α' (alpha). Incorrect choices regarding the rejection of the null-hypothesis are categorized into two types. The first error type corresponds to the significance level of 'α' and is a false positive. It describes the probability that the null-hypothesis is rejected despite being true and thus an outcome is discerned that is actually not real. The second error type, also called 'β' (beta), is a false negative. In such case, the researcher fails to identify an outcome that is actually existent. Due to the relation between the error types, reducing one results in the increase of the other. The basis on which the significance level is determined by the researcher deals with the dilemma of weighing confidence versus precision. The confidence level of a test expresses the likelihood of producing the same output in repeated testing and is formulated by one minus alpha. Lower significance levels therefore improve the confidence of a test. At the same time, though, lower values of alpha result in larger confidence intervals by including more values into the range in order to reach that higher level of certainty. Consequently, the precision of a test decreases. Academic research predominantly uses a significance level of five percent, including the particularly relevant studies referenced in previous chapters (e.g. Allison et al., 2017, Bi et al., 2017; Wang & Yang, 2019). Thus, this paper adheres to the collectively agreed balance between precision and confidence.

The data collection as well as the statistical analysis is executed with the help of computer-aided technology. A spreadsheet program features the ease of generating tables and similar. The comprehensive bibliography used for this research goes beyond those that are enclosed at the end of this paper and are accumulated in a large table including important notes and definitions extracted from the respective literature. In addition, the program serves as a tool to create other tables, some of which are integrated into this paper. Of particular importance is the data collection. The dataset is generated in form of a table in order to keep a structured overview of the vast number of variables accumulated. Additional variables are added that base on formulas about the data accrued, such as the ratio of first-time versus recurring backers and currency translations. The moderating variable of financial involvement is created and preliminary analysis regarding means and medians are performed. Afterwards, another software is used for statistical analysis of the data. IBM SPSS Statistics v.27 is an application suggested by the University of Twente as the institute also provides the required license for it. After the data is consolidated in a spreadsheet, it can be imported into SPSS. From there, the data is inspected for correctness and completeness and arrangements are made regarding labels and the like. With the groundwork done, statistical analysis can take place through graphical illustrations and statistical testing. However, first the following subsection gives more insight into the data itself, the operationalization and produces preliminary inspections before the empirical results are presented in the chapter to follow.

4.2 DATA

Information on the crowdfunding campaigns originate directly from the crowdfunding platform Kickstarter itself. Certain steps are taken in order to standardize the non-probabilistic approach and thereby reducing the impact of the shortcomings that come along with it. Especially the lack of reproducibility is a criterion that can be countered to a reasonable extent. Kickstarter's website offers a search functionality with several features that are essential to this process. Examples for filtering projects include how much the campaign raised compared to their goal and the campaign's geographical location. Although these filters posit interesting tools for backers, the one relevant to this research consists in picking the category a campaign falls under, in this case technology and product design. Despite the uncertainty as to who allocates projects into the 15 present categories and on what basis it happens, the list of categories is identical to the statistics about funding performance that Kickstarter publishes (cf. chapter 1.2). Thus a level of coherence is maintained within this paper.

Next, the sorting of the search results is changed towards the enumeration of campaigns descending in the amount of money pledged. The essential point about the approach lies in the fact that sorting based on an objective criterion avoids a dynamically-changing order that may happen with the default option (i.e. 'Magic'), which potentially is based on an adaptive algorithm. For the purpose of narrowing down the results to those relevant to this research, the search term "sustainability" is utilized. Alternative wording in form of "sustainable" or even "sustain" generate the exact same amount of projects, signifying adequateness. Terms such as "social", "green" or similar may qualify as additional words to use. However, the search word "social" generates vast results of diverse campaigns that do not explicitly address sustainability on first look. "Green" on the other hand produces only slightly more results compared to "sustainability". Yet, specifically targeting social entrepreneurship (Schaltegger & Wagner, 2011) or ecopreneurship (Schaltegger, 2002) leaves more room for interpretation and review as well as overlapping cases. In order to satisfy the ten percent assumption in inferential statistics, it appears more reasonable to extend the category of technology to also include the subcategory of product design. In that way compliance with the rule of thumb that the sample to population ratio is no more than 10% when not using finite population correction is satisfied by "sustainability" alone and it appears reasonable to focus on this only. So far, these steps improve the reproducibility in the data collection.

Since sustainability has been a topic of interest in marketing in recent years (Kemper & Ballantine, 2019), attention is given to distinguishing projects that actually refer to sustainable entrepreneurship. As a consequence, all campaigns are screened based on a simple, yet subjective, criterion of authenticity. Projects that mention sustainability or its discussed alternatives only as a buzz word are not eligible to be incorporated into the sample. The decision is based on various but straightforward possibilities to show commitment to the sustainable theme. These include implicit and explicit audiovisual or written cues that go beyond a single mention of the word for the sake of marketing (e.g. search engine optimization). Easy identifiers are the advertising of sustainable characteristics, relevant third-party certifications and personal motivation.

Examples for advertised sustainability within the sample are as follows. Typical advertised benefits regarding production and sourcing are upcycling and recycling of materials, organic ingredients, plastic and toxin-free products, fair-trade sourcing, manufacturers certified for environmental and labor standards, and a carbon-neutral footprint. When it comes to examples for sustainability during use, common themes are a reduction of consumption (e.g. energy, water), longer life-cycle by design, self-sufficiency (e.g. solar), reparability, reusability and ceasing the need for pesticides. At last, sustainable advantages post-use include recyclability and biodegradable components. The review of each campaign progresses through the list of projects according to the order mentioned. Consequentially, at first only high-performing campaigns are accrued. Yet due to the described low success ratio (cf. section 1.2), failed projects appear fairly soon and among these projects one additional decision is made. For the purpose of having a comparable and normalized sample, campaigns that were prematurely cancelled are not considered. Said differently, only projects that reach their set

Table 2
Categorization of variables

CATEGORIES	EXAMPLE VARIABLES
General information	Location, year, duration, funding success
Main campaign page	Word count, creator's education, patents
Campaign subpages	Update count, likes count, comments count
Pledges	Pledge options count, financial interval of pledges, funding goal
Sustainability	Sustainability advertised pre-, during and post-use
eWOM	Social media advertised, references, badge

runtime are incorporated. Once a project passes screening, a substantial amount of its content is categorized into variables explained below. The final sample size after preliminary analysis and cleaning concludes to a number of 50 cases of complete data points as explained in the rest of this chapter.

In order to aggregate the information, spreadsheet software is used with which a structured table is generated. All data is entered with consideration for ease of export into the statistics program SPSS, including the way of coding to comply with measurement levels and formatting. At first, variables are categorized into broader sets (see Table 2) for the sake of organizing and keeping track, these are: general information, main campaign page, campaign subpages, pledges, sustainability and electronic word-of-mouth. General information about the campaign are composed of the geographical location, the detailed time period (i.e. year, start and end date, duration in days), funding success and descriptive pointers. All of these are explicitly mentioned on the website and are objective. The unit of the campaign duration is days since Kickstarter states it in such manner and existing literature follows along (e.g. Belleflamme et al., 2014; Kuppuswamy & Bayus, 2017).

On the other hand, criteria are put in place for the data gathered from the main campaign page. Descriptive elaborateness (H1a) is operationalized as word count and is adapted from existing literature (e.g. Bi et al., 2017; Lagazio & Querci, 2018). The collection, however, is not straightforward despite the simple nature of its meaning. Kickstarter allows media to be placed within the text and creators take the opportunity to style their campaign page up to their liking. For some projects this only occurs for aesthetic appeal and barely makes a difference, others may seek a uniform look regardless of the display format (e.g. aspect ratio, resolution), for instance, and therefore go as far as transcribing almost all text into images. As a consequence, rules are established to standardize the collection. Unfortunately, the papers by Bi et al. (2017) and Lagazio and Querci (2018) do not seem to recognize this problem and thereby cannot serve as references for dealing with it. Hence, own choices have to be made. The baseline is the necessity to adapt to the differences in campaigns as little as possible in order to reduce influence through the researcher. Thus, text contained in images is only counted when it is not a direct repetition of the content above or below the image (e.g. repeating headlines), a commonly accepted image (e.g. logos), something that cannot be separated from the image (e.g. information on product colors next to their illustration) or does not add any remotely informational value. Confidence into the process is increased by recording the direct (i.e. text) and indirect (i.e. transcribed from image) word count as dummy variables and only then summing them up into a total word count. Median and mean for text-only are 1173.0 and 1314.4 words compared to 1305.5 and 1429.1 words for the total. The differences between the two variables seem justifiable when opposing this with an extreme case, in which a campaign only had 165 words written in plain text and another 925 transcribed graphically. Such outcome seems inappropriate, particularly because the words contained inside the images are long paragraphs that clearly stated coherent text relevant to the project. A project with an almost identical score for both dummy variables features a ratio of 268 to 216 words, as well as another one being 981 to 707. Yet most of the campaigns exhibit a clear tendency towards non-transcribed text which is visible through a median of 39 and a mean of 114.7 for the transcribed word count, thereby indicating that flaws and bias by the researcher may not be a too large threat.

Adjoining the rationale of word count, images are included as a control variable and also require decision-making. In accordance, illustrations are not counted if the image bears very little contribution to the campaign (e.g. colored separators between paragraphs) or form a coherent flow with adjacent graphics and thereby aggregated as one. Despite the subjectivity, the variable's role is only of controlling interest and its median (13.5) is almost identical with its mean (13.6) so no further concerns about empirical results are expected. Staying on the topic of media, the amount of videos (H1b) is counted, as well, and its median (2.0) and mean (2.4) are both around two. In alignment with the study of Bi et al. (2017), counting more than just the primary video, also known as the pitch, is an extension of the more common dichotomous approach of whether it exists or not (e.g. Cordova et al., 2015; Lagazio & Querci, 2018; Mollick, 2014). In addition, the length of all videos within a campaign page are enumerated, following the lead of Davis et al. (2016) in incorporating it as a control variable. Here, the discrepancy between median (180.5) and mean (288.4) is actually notable. Another relevant control variable categorized under the main page refers to whether the creator makes the effort of following Kickstarter's suggestion by implementing a segment of risks and challenges. The only divergent decision made here is an adjustment of one project, in which the section is present in the form of a single sentence with no mentionable effort recognized and hence coded as non-existent. All other campaigns are coded strictly on presence alone. Moreover, two additional control variables include external third-party certifications as well as advertised patents that are either pending or registered. Both are coded in simple binary terms representing their presence or absence respectively and are straightforwardly ascertained without the need of subjective assessment.

Further variables categorized under the main campaign page concern the entrepreneur's ability. Education has been part of research on crowdfunding for many years yet its implementation as a variable varies (cf. Ahlers et al., 2015; Allison et al., 2017; Butticè et al., 2019; Davis et al., 2016; Wang & Yang, 2019). To avoid researcher-based judgement regarding qualifications, this paper operationalizes education (H2a) in the form of whether the entrepreneurs disclose their educational background or not. This leaves the interpretation to the investors and makes the variable a binary statement of whether the backers are provided with the possibility to do so or not. The same logic applies to the variable of professional expertise. Zhou et al. (2016) define experience as the number of previous campaigns and expertise as the number of those completed successfully. However, collection of such information comes with obstacles. Entrepreneurial teams can change on a project basis, profile accounts can be deleted or changed, accounts used for the creation of the campaign can be substituted with individual or company accounts and other platforms can be used in previous projects, too. As a consequence, data on previous campaigns appear low in comparability unless discussed within the campaign description itself. Hence, a broader definition of professional expertise is taken in form of a dichotomous variable noting whether the entrepreneurs state their relevant skillset and experience (H2b) within the text themselves. This bears rough resemblance to the approach of Cho and Kim (2017). Once again, this transfers the responsibility of assessment to the backers. Still, to comply with previous research, a dummy variable for experience is produced in which the number of previous campaigns is enumerated by referencing the account history of the campaign creator. An additional web-search is executed to crosscheck potentially overlooked campaigns due to aforementioned reasons but a deep research is not feasible and leaves this as a control variable only. As an extension regarding human capital, a control variable is incorporated in the form of whether information about the rest of the team is featured or not. The rationale is based on previous research that emphasizes its importance as already the number of people involved has impact (Ahlers et al., 2015; Bento et al., 2019b; Lagazio & Querci, 2018).

Information around the cues backers can obtain when it comes to financial options are categorized under pledges. Petruzzelli et al. (2019) suggest that more price points for investors to choose from may make a difference, especially if the entry is lower in the beginning of the campaign. Consequently, the number of pledges per campaign are counted and possess a median of 9.0 and a mean of 10.3. Along with it also the financial interval is recorded and covers the lowest to highest amount of money that a backer can choose to invest. Naturally, the differences in mean and median are greater in these variables, which receives more attention below when addressing financial involvement as a moderator. The reference to the respective moderator also plays a role with regards to the amount pledged along with the amount of backers, though. Both are stated by Kickstarter at the end of the campaign and are therefore eligible as reference points because figures beyond the campaigns' original runtime would distort the differences between successful and failed projects. Preference for the dependent variable is given to the amount of backers for multiple reasons. The research model (see Figure 1) visualizes funding intention as the center of attention. In other words, this study aims to investigate how each backer is affected in the decision-making process. Money invested may be a proxy for this yet the actual amount of backers appears to be much more appropriate while even readily available. Especially when considering that it avoids conflict with the moderator of financial involvement, is less distorted by variations in pricing since pledge options in the sample range from as low as 1 US dollar to as high as 10000 US dollars, exhibits lower values to work with in the regression and offers more direct interpretations. The choice of a continuous variable in general also makes for an advantage over logistic regression, which would only distinguish between failure and success in the dichotomous variable created and is unable to integrate the underlying variances in money or backers already collected. Furthermore, the funding goal is gathered and also the currencies for each campaign are listed in a separate dummy variable. Required exchange rates for the financial variables were accessed via XE.com (XE.com Inc., 2021) within moments apart on the same day. This appears as a fair-enough simplification, albeit keeping in mind that the prices are also not truly standardized due to time value of money.

Both moderating variables, viz. financial involvement and backers' experience, are computed via other variables as demonstrated by relevant academic research (Allison et al., 2017). With reference to campaign characteristics, the division into low (H5a) or high (H5b) financial involvement follows the approach of Allison et al. (2017) by relying on the median value of the least expensive pledge. Lowest and highest prices for pledges are scraped from each campaign page as mentioned and translated into USD. The US dollar represents the unit of choice because it constitutes the default currency for nearly half (46%) of the sampled campaigns, as well as it being considered the world's lead currency (Chiţua et al., 2014). Another third of the campaigns are based on euros (30%) and the remaining 26% are split between smaller shares as seen in Table 3. The sample's median for the least expensive pledge consists in five US dollars and serves as the cut-off point between low (≤5) and high (>5) financial involvement, coded into a dichotomous variable each. It should be noted that Allison et al. (2017) calculated the median not only based on the sample but drew numbers from a larger subset thanks to their technology-aided approach. Unfortunately, this is not feasible for this study, yet the mean and median values for the lowest-priced pledges are rather similar between the studies, still. For this sample, the mean for the lowest-priced pledge was 49.90 US dollars overall, 2.40 US dollars for the group allocated to low financial involvement and 60.90 US dollars for those campaigns featuring high financial involvement. The second moderator refers to the backers' attributes, namely their level of experience (H6), and is also adapted from the study of Allison et al. (2017). For most campaigns, Kickstarter states not only

Table 3

Currencies chosen by campaigns

CURRENCY	N	%	CUM. %
USD	23	46.0	46.0
EUR	15	30.0	76.0
GBP	3	6.0	82.0
CAD	2	4.0	86.0
CHF	2	4.0	90.0
SEK	2	4.0	94.0
AUD	1	2.0	96.0
HKD	1	2.0	98.0
JPY	1	2.0	100.0
Total	50	100.0	100.0

the total amount of backers at the end of the campaign but also their division into first-time and recurring investors. This allows for calculating the ratio between the two. Thus, the self-computed variable of high backers' experience is stated in binary form and denoted as zero when more first-timers are among the investors and one when a campaign features more recurring than first-time backers.

The next denomination consists in sustainability and requires individual assessment. The sustainability orientation (H4) of entrepreneurs and their respective project is operationalized in explicit marketing of sustainable characteristics, similar to Calic and Mosakowski (2018) and with the help of keywords exemplified by Bento et al. (2019b, p. 5). Three dummy variables of dichotomous nature are generated that roughly correspond to product life-cycle stages. An additional dummy of string format is included and details which claims are made for each of the stages. For simplification, only three phases are differentiated. Advertised sustainability during production considers everything from product idea, material sourcing, manufacturing, logistics and the like. Examples are elaborated earlier in this section; the most common refers to ingredients (e.g. organic, plastic-free, toxin-free, recycled, upcycled). After production, the period during usage is included as a dummy variable. Most common sustainability benefits highlighted in this variable concern a reduction in resource consumption (e.g. electricity, water) or the autonomy thereof (e.g. solar). At last, goods need to be discarded at some point, and the dummy variable of advertised sustainability post-use predominantly enumerates the recyclability and biodegradability of components. Through the generation of so specific dummy variables, the researcher is forced to pay attention to details and needs to scan every campaign three times due to the coding of three separate dummies. It also results in an increase in the number of control variables. This allows additional testing and lifts confidence regarding the subjective nature of the task. The combination of the three variables synergizes into the final variable used in the model and states whether any form of sustainability is advertised or not.

When it comes to social capital, different approaches have been taken in past research. Papers on Social Capital Theory as well as Social Network Theory in the field of crowdfunding set an emphasis on the networking aspect in terms of, both, internal (Colombo et al, 2015) and external (Kang et al., 2017; Zheng et al., 2014). The omission by Kickstarter regarding the Facebook Like button that previous studies utilized (Bi et al., 2017; Mollick, 2014), shifts the attention to social networking. Since it is not within the scope of this study to monitor real-time data of ongoing campaigns however, it is also not feasible to incorporate multiple variables that may otherwise be of interest. Particularly, variables concerning electronic word-of-mouth within social platforms would else be an area of opportunity. In case of social media activity, for instance, it means that information about a campaign's digital momentum are not possible to be collected. Without the (technical) ability to go back in time, it is not feasible to identify how many reactions a campaign received in form of sharing, liking or commenting across different platforms throughout the relevant time period. The same applies to the idea of social capital in terms of the creator's own digital network size (e.g. Mollick, 2014) or the online audience involved in the campaign (e.g. Colombo et al., 2015). However, proxies are gathered for the sake of some sort of completeness and curiosity, viz. publicly available data about the company profile pages obtained from multiple social media websites. These include the amount of likes and followers on Facebook, number of posts and followers on Instagram and Twitter, subscriber count and total view time on YouTube, and followers on LinkedIn. The choice regarding these platforms are based on literature in both eWOM and crowdfunding, such as Yang and Berger's empirical study from 2017, in which the authors highlight the importance of Twitter and Facebook in financing start-ups. A respective article that systematically reviews social media within the sphere of entrepreneurship consists in the one by Olanrewaju et al. (2020), in which the authors enumerate Instagram's large base of users following business accounts, the division between professional and social networks, YouTube's comparably low activity, the importance of network size and the audience's active involvement, among others.

Nonetheless, some data within the campaign refer to matters of electronic word-of-mouth and social capital that creators decide to implement themselves. These serve as proxies for the actual social buzz around a campaign. Naturally, this is an alternative approach that is only a rough estimation and biased. However, entrepreneurs that are aware and engaged in social platforms are more likely to integrate them into their business strategy (Raman & Menon, 2018), so this approach seems fair considering the limited resources for this research. Proxies computed consist in objectively gathered variables coded in binary form (0=no, 1=yes). The social platforms advertised (H3b) by the entrepreneur on a campaign page make for the first variable. A concomitant dummy with text content (i.e. string format) describes which platforms are specifically advertised. This dummy reveals a surprising find in that the predominant social network advertised is Instagram with 19 observations, followed by Facebook with 14. Facebook has received primary recognition in academic literature so far (Bento et al., 2019b; Candi et al., 2018; Colombo et al., 2015; Lagazio & Querci, 2018; Mollick, 2014; Wessel et al., 2016) with Instagram gaining attention more recently (Olanrewaju et al., 2020). This could be a hint towards the dynamic in the digital sphere that research may inadequately address and ought to better consider. Moving on, any specific inquiries by the entrepreneur for the audience to participate in digital social interactions is computed as explicit eWOM encouragement. Direct representations of eWOM are aggregated through the next two variables. References (H3c) incorporated into the campaign page that mention press coverage in either indirect (i.e. logos only) or direct (i.e. incl. excerpt) form, comments from other verifiable third-parties as well as campaign-related awards are combined into one binary variable and a string-based variable detailing the observation. In alignment with the common notion of eWOM research that online reviews affect decision-making (e.g. Cheung & Thadani, 2012), the presence of any external product review on the campaign page is denoted in dichotomous form with yet again an explanatory variable stating the form of review. It should be noted that while both variables concerning external content are objectively collected into the dataset, their actual authenticity is under the influence of the campaign creator and therefore bias is a threat to consider and elaborated further in the limitations section later (cf. chapter 6.3). Another control variable with regards to eWOM consists in Kickstarter's "Project's We Love" badge. It is an official badge that campaigns can be awarded with when they satisfy undisclosed criteria by Kickstarter's own staff. So far no academic literature has tested this but it is included in Kickstarter's search options and weighs heavy enough for it to be an individual filter to select. The rationale behind this badge for the sake of this research constitutes in Kickstarter's opinion being a signal in the form of electronic word-of-mouth.

The last set of variables also partake in the eWOM theme but are based on the subpages of the campaigns. Kickstarter offers additional subpages besides the introductory section (i.e. main campaign page) on which the project is described. Always present on each campaign are the subpages for updates and comments in which only creators and backers are eligible to actively participate. Although dummy variables are gathered for the time period post-campaign as well as total, the relevant variables for hypothesis testing are limited to the original campaign runtime. The number of updates, the likes as well as the comments (H3a) on the updates are manually counted and coded into a continuous variable each. Examples in literature for update and comments count include the papers of Kim et al. (2017) and Kuppuswamy and Bayus (2017). The highest update like count for a single project is 2542 without the time restriction (i.e. total). Counting only until the campaign's end the number maxes out at 366. Analog to the likes, also the comments exhibit a substantial difference in maximum values for a single project when comparing between campaign end (162) and date of data collection (3594). Less severe is the comparison for the update count. The project with the most updates posted during the campaign's runtime lies at 20, whereas those projects that are successful reach a maximum of 52 until the time of data collection. Although the total for the comments section is collected as a dummy variable, it does not add to the research other than its descriptive statistics concerning the mean (11.5), median (313.5) and maximum value (5408). Manually going through the comments section is not only impractical regarding resource allocation but also technically restricted on the side of Kickstarter as quick skimming through all comments generates stress on Kickstarter's servers that causes automatic defenses against bots to slow down or even completely stop the process. Additional dummy variables are computed in the form of an average number of likes as well as comments per update. The former exhibits a median of 2.0 and a mean of 5.2, with the latter being lower with a median of 0.5 and a mean of 2.2.

All data accrued in the spreadsheet software is then exported to SPSS. The dataset is screened for completeness and formatting of variables is finalized. The definition of measurement levels and their values are particularly noteworthy among the many other steps. Naturally, dichotomous variables are made of two definite values. Variables that describe the presence of something in binary terms therefore follow the approach of denoting 0 for "no" and 1 for "yes", which is in line with other academic literature (e.g. Allison et al., 2017). Regarding the variables within the research model, this coding is applied to education (H2a), expertise (H2b), social platforms advertised (H3b), references (H3c), sustainability orientation (H4), financial involvement (H5) and backers' experience (H6). The remaining variables in the research model, viz. descriptive elaborateness (H1a), video count (H1b), comments (H3a) and the dependent variable of amount of backers, are characterized as continuous, or scale in SPSS terminology, and are also formatted numerically. Descriptive variables are entered with nominal measurement and a string format. Two examples consist in the currency chosen (see Table 3) and geographical location (see Table 4).

After preparing the dataset, a review of its coding is conducted. SPSS features an overview of all variables and how they are recorded in the form of what is termed a 'codebook'. Its generation allows for the first indication of a functional dataset. At this point, the dataset is not yet reduced to its final sample size. Instead, the accumulated data contains variables with very few missing values that are unavailable during collection, exemplified by four campaigns for which Kickstarter does not provide the amount of first-time versus recurring backers for undisclosed reasons. Despite a nearly complete dataset, attention is still given to maximizing the cases included in order to influence the outcome and power of preliminary tests as little as possible. In SPSS this is achieved by excluding missing values on an analysis-by-analysis basis as well as choosing a pairwise exclusion over 'listwise'. This means that tests are run with the most cases possible for each respective test and that exclusion is only done to those cases of variables that are specifically tested together (e.g. Pearson Correlation) instead of taking missing values out for tests and variables that individually would not be affected. This is applicable for the preliminary phase of getting to know the data in a trial and error manner. It allows the inclusion of observations that would otherwise be overlooked in a 'listwise' approach. Fortunately, no relevant changes are notable and therefore the number of cases is reduced to the aforementioned 50 cases that include data points for all variables inspected in order to reach a single, complete dataset. Thus, the most complex model tested in hierarchical regression serves as the base to test all other models that include fewer independent variables. With a final sample size of 50 cases it can be argued that the Central Limit Theorem is satisfied along with the suggestion that linear regression requires a minimum of two cases per variable tested (Austin & Steyerberg, 2015). This also underlines the choice for a linear regression instead of a logistic regression since the latter presumes a larger sample size considering the amount of predictors.

Reviewing the methodology section, the process of collecting and preparing the data is described and the foundation on the execution of the statistical analysis is laid out. The dataset is checked for obvious errors and missing value and special attention is given to self-computed variables to minimize personal mistakes. Eventually, the dataset is reduced by a few cases that cannot meet the requirements and hence the sample is finalized with a number of 50 individual campaigns.

5. EMPIRICAL RESULTS

The fifth chapter demonstrates the empirical part of the study. The hypotheses summarized in Figure 1 are investigated with the help of the methodological approach elaborated in the previous chapter. At first, descriptive analyses and preliminary tests are addressed to improve the comprehension of the data and assure the appropriateness and proper execution of the regression. Afterwards, regression results are presented and checks of robustness are discussed.

5.1 DESCRIPTIVE RESULTS

Kickstarter is a platform based in the United States of America and therefore exhibits a primarily western basis. The breakdown of the location of the campaigns aggregated (see Table 4) reflects this well because all (ca. 92%) but four (ca. 8%) out of the 50 projects are established in a western country. Albeit only four campaigns officially disclose Asian cultures (viz. Hong Kong, Israel, Japan, Singapore, Taiwan) as their origin, a deeper dive into the company and founder background reveals that there are at least four additional projects within the sample that may descend from East Asia – changing the ratio percentage to approximately 84-16. Since this still means that more than four fifths of the campaigns share a primarily Western background, this research conforms to the initial objective to add to the work of Bi et al. (2017), who studied a predominantly Asian setting instead.

Table 4

Geographical distribution of campaigns

COUNTRY	N	%	CUM. %
USA	20	40.0	40.0
Germany	8	16.0	56.0
Sweden	4	8.0	64.0
Switzerland	3	6.0	70.0
Canada	2	4.0	74.0
Netherlands	2	4.0	78.0
Great Britain	2	4.0	82.0
Rest	9	18.0	100.0
Total	50	100.0	100.0

A look at the original airing of the campaigns offers insight on how current the dataset is. Table 5 displays that 20 (40%) out of the 50 projects were launched within the last two years, i.e. 2020 and 2019. Adding an extra two years, namely 2018 and 2017, the number rises to 32 (64%) campaigns. Thus, approximately two thirds of the sample dates back the past four years. In accordance, the dataset can be argued to be fairly recent. Additionally, the table indicates an accelerating growth in sustainable-oriented campaigns, which complements the previously explored trend (cf. section 2.4) because the increase in popularity of sustainability entrepreneurship over the last years is existent in the

Table 5

Years of campaigns launched

YEAR	N	%	CUM. %
2020	10	20.0	20.0
2019	10	20.0	40.0
2018	7	14.0	54.0
2017	5	10.0	64.0
Rest	18	36.0	100.0
Total	50	100.0	100.0

collected sample. In other words, its pertinence outside of academic research is evident in the form of practical examples and consequentially gives credit to the relevance of this paper.

Staying on the topic of time, the interval a campaign originally runs has been a subject of academic attention (e.g. Kim et al., 2017) and should be included as a control variable. Table 6 discloses 30 days as the predominant choice of creators because the 19 corresponding projects account for more than a third (38%) of the sample. The next individually most frequent duration, 35 days, makes up for only 5 cases (10%), followed by 45 and 60 days with 4 cases (8%) each. It offers support to a well-established notion of 30 days being the norm in the crowdfunding sphere (Kuppuswamy & Bayus, 2017; Mollick, 2014). Allocating all campaigns into groups may provide a better glimpse of the data: 24 (48%) projects are shorter or equal to 30 days, 18 (36%) are between 31-45 days and only 8 (16%) are longer than 45 days. Said differently, about half of all projects end within the common 30 days, while a notable third runs as far as fifty percent longer and only a few campaigns reach the platform's limit and extend the runtime to double of what is most prevalent. When comparing the most frequent (i.e. 30 days) campaign length with those farthest away (i.e. 60 days), it is notable that the success rate is very similar. Exactly half (50%) of the four campaigns that ran for two months were a success, whereas 11 (ca. 58%) of the 19 that ran for one month got funded and performed slightly better. While not probative on its own, it is a pointer towards a lack of relevance as a determining factor and backs up the decision to only include the length of a campaign's runtime as a control variable.

Table 6

Overview of campaign duration

DAYS	N	%	CUM. %
30	19	38.0	38.0
35	5	10.0	48.0
45	4	8.0	56.0
60	4	8.0	64.0
Rest	18	36.0	100.0
Total	50	100.0	100.0

Continuing on that subject, campaign performance represents one of the more apparent data points and, in its simplistic form, can be divided into a dichotomous variable. In that sense, the overall ratio between successful and failed campaigns is 17 (34%) to 33 (66%) and results in a skewness of -0.697. This rate aligns with Kickstarter's overall statistics on successfully completed projects (ca. 38%) yet this number decreases to approximately 20% when focusing on technology goods as previously discussed (Kickstarter, PBC, 2021; Liang et al., 2019). Therefore, the sample fits in between officially reported figures and while it does not serve as evidence for overcoming limitations of a non-probabilistic study, it does imply that the lack of proper randomization in this study does not automatically erase all generalizability, either.

Simple tables (i.e. frequency, descriptive) and graphs (i.e. boxplot, histogram, scatterplot) are produced for every other variable, too, in order to get a holistic understanding of the data. Visualizing each variable individually reveals that very few observations are notably off the rest of the dataset. Inspecting the cases across variables shows a pattern of, in comparison, extremely successful campaigns generating very high numbers in expected variables such as the amount of backers and the amount of money pledged. Yet only one campaign actually requires attention in terms of possible exclusion due to being an extreme outlier.

Table 7

Descriptive statistics

Variables	Mean	Median	Std. Dev.	Skewn.
DV	930.400	155.000	2182.302	4.101
LN(DV)	5.159	5.043	1.868	0.379
1	1429.680	1305.500	777.810	0.980
2	2.480	2.000	2.306	2.982
3	12.420	2.000	30.456	3.731
4	0.920	1.000	0.274	-3.193
5	0.380	0.000	0.490	0.510
6	0.160	0.000	0.370	1.913
7	0.260	0.000	0.443	1.128
8	0.500	0.500	0.505	0.000
9	0.440	0.000	0.501	0.249
10	0.720	1.000	0.454	-1.011
11	0.160	0.000	2.095	3.710

Independent Variables (IV): 1 = Word Count; 2 = Video Count; 3 = Comments Count - Updates Section - During Campaign; 4 = Advertised Sustainability; 5 = Social Platforms Advertised; 6 = Education; 7 = Expertise; 8 = References; 9 = High Backers' Experience; 10 = High Financial Involvement; 11 = Interaction: Video Count (Centered) x High Backers' Experience
Dependent Variable (DV): Amount Of Backers At End Of Campaign

A common criterion in the decision-making is the notion that observations should not exceed the range of three standard deviations (Jones, 2019). Despite its advantage of ease, this method is not the most accurate and also presumes normal distribution. With reference to the research model the only relevant variable with an extreme outlier is the Amount Of Backers At End Of Campaign. Considering that the observations in this variable are not normally distributed, as visually presented in Figure 2, but strongly skewed to the right, as also numerically expressed in Table 7, a different approach is taken. The strong skewness and thereby the extremity of the outlier can be countered with a logarithmic transformation of the dependent variable. In this case, the natural logarithm is applied, although the same can be achieved with a base of 10, for instance. Generally, outliers should not be excluded from a dataset unless they are either an error or affect the data unjustifiably much. When comparing the outlier within the sample to the larger population by skimming through non-sampled campaigns on Kickstarter, it becomes apparent that the outlier does not pose an abnormal value but is rather a proper representation of a successful project. This is underlined by the fact that the campaign in question is falling short of the 300 most backed projects on the platform, as can be checked by filtering all campaigns by the amount of backers at the end of a campaign on Kickstarter's website. Log-transforming the dependent variable reduces skewness from 4.101 to 0.379 (cf. Table 7), and thereby shifting towards a fairly normal distribution as visible when comparing Figure 2 and Figure 3. Although linear regression does not require the individual variables to follow a normal distribution, the logarithmic transformation of the dependent variable is critical for the residual analysis and to be addressed in section 5.3.

Figure 2

Histogram of DV before log-transformation

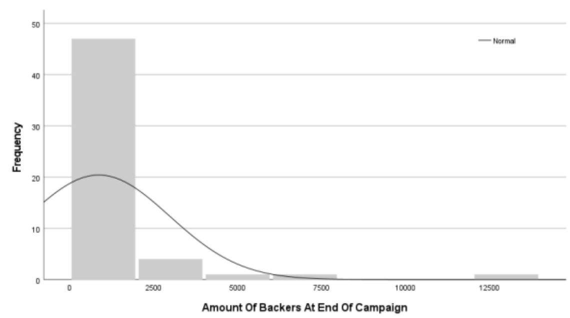
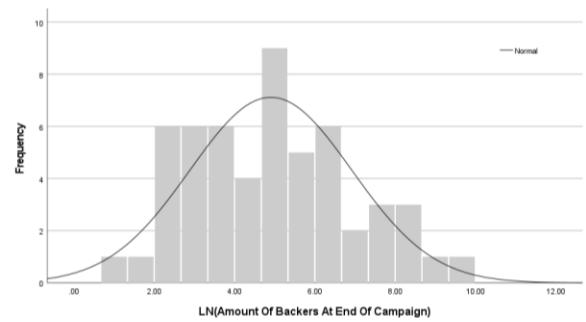


Figure 3

Histogram of DV after log-transformation



The table reporting descriptive statistics (i.e. Table 7) indicates that also the other three continuous variables are skewed to the right, namely Word Count with 0.980, Video Count with 2.982 and Comments Count- Updates Section - During Campaign with 3.731. Transformations of these variables do not create similarly relevant effects, however. While reducing the large values of Word Count (mean: 1429.680; median: 1305.500; standard deviation: 777.810) to be more in line with the other variables, the skewness for Word Count changes from slightly positive (i.e. right) to slightly negative (i.e. left), without relevant differences during trials of statistical testing. The values for the other two variables with metric measurement levels are already matching the overall scale of the rest and their logarithmic transformation does not make much of a difference there. The topic of interest lies in the skewness, instead. Yet, as both variables include values equaling zero, a log-transformation results in no relevant advantage and hence is dismissed. The similar but more extreme case occurs with the rest of the variables due to their dichotomous nature of equaling either zero or one.

The descriptive statistics provide further interesting findings albeit limited by the categorical nature. Almost all campaigns specifically advertise their sustainability benefits, adumbrated by a mean of 0.920, a median of 1.000 and the lowest standard deviation in the model with 0.274. The opposite is the case for the independent variables of Social Platforms Advertised (mean: 0.380), Education (mean: 0.160), Expertise (mean: 0.260) and the suspected moderator High Backers' Experience (mean: 0.440), which all feature a median of 0.000. The variable References is the only one in the model with distinctly symmetrical data (skewness: 0.000), also visible through an identical mean and median of 0.500. Skewness of these variables ranges from strongly negative (i.e. −3.193) to almost as strongly positive (i.e. 1.913). The categorical coding of these variables results in dismissal of further relevance. Especially since categorical measurement levels are typically not appropriate for analyzing means and the like. The rationale is similar when it comes to the assumption of linearity.

As the name implies, linear regression presupposes a linear relationship. Although capable of modelling curvilinear relationships (e.g. quadratic via polynomial terms), regular linear regression describes its function in a linear form. To ensure compliance with this assumption, linearity between dependent and independent variables needs to be checked before executing the regression. Since dichotomous variables only model either zero or one, no linear relationship can be visualized via scatterplots or typical mean-based correlations. Hence, the linear regression tests for individual variables are limited to those of metric measurement and delineated through the correlation coefficient 'R', which describes the linear relationship between two metric variables in terms of the intensity as well as the direction.

Table 8

Linearity checks

	DV		LN(DV)	
IV	R	Sign.	R	Sign.
1	0.471	0.004	0.343	0.031
2	0.512	0.000	0.087	0.267
3	0.754	0.000	0.601	0.000

Independent Variables (IV): 1 = Word Count; 2 = Video Count; 3 = Comments Count – Updates Section – During Campaign
Dependent Variable (DV): Amount Of Backers At End Of Campaign

As visible in Table 8, the correlation between the Amount Of Backers At End Of Campaign and the Word Count (R=0.471), Video Count (R=0.512) and Comments Count – Updates Section – During Campaign (0.754) is very high and statistically significant at a $p<0.01$ level. After log-transforming the dependent variable this correlation reduces for Word Count (R=0.343) similarly as for Comments Count – Updates Section – During Campaign (R=0.601) while both still remain statistically significant (i.e. $p<0.05$). Unfortunately, Video Count (R=0.087) loses its individual linear relationship with the dependent variable and is no longer significant. Accordingly, a compromise is reasoned in the form of adding additional steps within the hierarchical regression analysis: on one hand to include the predictor to still test the full research model as originally designed; and on the other hand to exclude the variable in other models to address the lack of linearity with the log-transformed DV.

5.2 HIERARCHICAL LINEAR REGRESSION

Throughout the execution of the regression part many additional steps are taken in both forward and backwards manner. The trial and error approach deepens the investigation by including control variables and addressing the issue of confounding variables, for instance. As previously elaborated (see section 4.1), algorithm-based stepwise regression is a useful technique in distinguishing among a larger set of variables and narrowing down to those contributing the most to a model. A particularly notable finding in this process is the predictive power attributed to all variables concerning the updates subpage of a project, viz. Update Count – During Campaign, Likes Count – Updates Section – During Campaign and Comments Count – Updates Section – During Campaign. However, manually testing these variables together within smaller and bigger models reveals light indications of multicollinearity, signified by higher numbers for the variance inflation factor (VIF) compared to other regressors. Their significance values also vary depending on how many of the three variables are included, which reflects their mutuality. This may be explained in the rationale that the variables are not absolutely independent of each other considering that more updates provide more opportunities for the same group of people to like and comment.

Table 9

Simple linear regression results

	INDIVIDUALLY AGAINST DV		
IV	β (Std.)	Sign.	R^2 Adj.
1	0.300	**0.027**	0.073
2	0.142	0.306	0.001
3	0.338	**0.000**	0.325
4	0.132	0.343	0.000
5	0.311	**0.022**	0.079
6	0.338	**0.013**	0.097
7	0.263	0.055	0.051
8	0.461	**0.000**	0.198
9	0.203	0.157	0.021
10	0.551	0.329	0.000
11	0.129	0.371	0.000

Independent Variables (IV): 1 = Word Count; 2 = Video Count; 3 = Comments Count – Updates Section – During Campaign; 4 = Advertised Sustainability; 5 = Social Platforms Advertised; 6 = Education; 7 = Expertise; 8 = References; 9 = High Backers' Experience; 10 = High Financial Involvement; 11 = Interaction: Video Count (Centered) x High Backers' Experience
Dependent Variable (DV): Amount Of Backers At End Of Campaign (Log-Transformed)

Comments is shown to be a strong individual predictor with a standardized β coefficient of 0.338 at a significance level of $p<0.001$ (see Table 9). Its R-Squared Adjusted value claims for the variable to account for at least 32.5% of the variability in the amount of backers at the end of a campaign. Hence, it is argued for the variable to stay within the hierarchical regression testing and dismiss the other two control variables with a recommendation for future research. Besides comments, also the advertising of social media is highlighted within the automated stepwise regression. A separate simple linear regression for this regressor reports a similar standardized beta coefficient (0.311) with a p-value of below five percent (see Table 9). The explanatory power of this variable (R^2 Adj. = 0.079) is substantially lower in separate regression compared to the comments count, though.

Individual regression tests are also executed for the rest of the independent variables within the research model. The results unveil two more regressors that are similar in predictive strength compared to Social Media Advertised: Word Count (R^2 Adj. = 0.073) and Education (R^2 Adj. = 0.097). The former is on the lower versus the latter on the upper side, with Social Media Advertised coming in between. The same holds true for the standardized beta coefficients (Word Count: 0.300, Education: 0.338) and the p-values. The last statistically significant variable produced via simple linear regression with the log-transformed dependent variable is References. It features the highest standardized beta coefficient (i.e. 0.461) among the individual tests. With $p<0.001$ the variable is alike Comments Count – Updates Section – During Campaign. Despite not reaching the same predictive strength, its R-Squared Adjusted value of 0.198 is still remarkable on its own. Hence, simple linear regression produces two highly relevant predictors.

Moving from preliminary analysis to hierarchical regression, the results are depicted in Table 10 below. While the table still displays regular R-Squared it is not mentioned further and reasoned as follows. R-Squared resembles the part of the model whose variance can be explained by the variables included. Its value increases with every independent variable subjoined regardless of any statistically significant contribution. This can be argued as an incentive for researchers to append too many predictors and is also known as overfitting a model. R-Squared Adjusted and the F-Statistic are useful in countervailing this issue. The larger the number of variables included in a regression, the higher the probability of reaching statistical significance simply by chance. With R-Squared Adjusted and the F-Statistic the number of independent variables are taken into account and adjustments occur to counteract potential bias. Similarly, R-Squared Adjusted is a more conservative method for extrapolating the sample towards the population. Both numbers can also actually decrease when a variable does not fit the model well and stands in contrast to regular R-Squared, which either remains the same or awards the inclusion of additional variables. Accordingly, R-Squared Adjusted is emphasized instead of R-Squared, which is still stated for completeness.

The following table is organized in a coherent manner from left to right. It starts off with the largest amount of variables as described in the research model (Figure 1) and concludes with only statistically significant predictors remaining in the last model.

Table 10

Hierarchical regression results

		MODEL 1		MODEL 2		MODEL 3		MODEL 4		MODEL 5		MODEL 6	
		β (Std.)	Sign.	β (Std.)	Sign.	β (Std.)	Sign.	β (Std.)	Sign.	β (Std.)	Sign.	β (Std.)	Sign.
IV	1	0.019	0.870	0.150	0.901	0.082	0.476	0.030	0.792	0.091	0.428	–	–
	2	−0.194	0.087	−0.104	0.464	−0.197	0.087	−0.106	0.351	–	–	–	–
	3	0.491	<u>0.000</u>	0.565	<u>0.000</u>	0.524	<u>0.000</u>	0.572	<u>0.000</u>	0.552	<u>0.000</u>	0.520	<u>0.000</u>
	4	0.008	0.943	−0.012	0.911	0.016	0.888	−0.011	0.918	0.064	0.553	–	–
	5	0.269	<u>0.016</u>	0.299	<u>0.007</u>	0.280	<u>0.014</u>	0.304	<u>0.006</u>	0.245	<u>0.026</u>	0.279	<u>0.007</u>
	6	0.131	0.321	−0.054	0.682	0.102	0.445	−0.060	0.645	0.086	0.520	–	–
	7	0.160	0.189	0.178	0.170	0.130	0.286	0.166	0.188	0.167	0.170	–	–
	8	0.212	0.058	0.255	<u>0.031</u>	0.226	<u>0.047</u>	0.255	<u>0.029</u>	0.213	0.066	0.307	<u>0.004</u>
	9	0.177	0.119	–	–	0.145	0.195	–	–	–	–	–	–
	10	0.192	0.094	0.051	0.642	–	–	–	–	–	–	–	–
	11	–	–	–	–	–	–	–	–	−0.185	0.121	–	–
MODEL	R^2	0.638		0.563		0.614		0.560		0.596		0.530	
	R^2 Adj.	0.545		0.473		0.527		0.482		0.518		0.502	
	F	6.866		6.289		7.074		7.172		7.574		18.822	
	Sign.	0.000		0.000		0.000		0.000		0.000		0.000	

<u>Independent Variables (IV)</u>: 1 = Word Count; 2 = Video Count; 3 = Comments Count – Updates Section – During Campaign; 4 = Advertised Sustainability; 5 = Social Platforms Advertised; 6 = Education; 7 = Expertise; 8 = References; 9 = High Backers' Experience; 10 = High Financial Involvement; 11 = Interaction: Video Count (Centered) x High Backers' Experience

<u>Dependent Variable (DV)</u>: Amount Of Backers At End Of Campaign (Log-Transformed)

The execution of simple linear regression on the independent variables concluded by highlighting two very strong predictors (cf. Table 9). The outcome for the multiple linear regression of Model 1 confirms these two variables (cf. Table 10). Comments Count - Updates Section - During Campaign as well as Social Media Advertised exhibit both high standardized beta coefficients and are statistically significant at $p<0.001$ as well as $p<0.05$ levels. Alike individual testing, comments provide higher beta values, yet it is much more pronounced in the model. Unlike individual testing, no other regressor achieves statistical significance. The only one that just failed to reach significance ($p=0.058$) is References, which possesses the third highest coefficient (0.212). Surprisingly, the amount of videos is negatively related and features a standardized beta coefficient of -0.194. It constitutes the only independent variable in the model with such direction. Moreover, Word Count and Advertised Sustainability do not play any role, while the variables concerning the entrepreneur's ability feature notable standardized beta coefficients but are clearly not statistically significant either. The same applies to both supposed moderators, which are integrated without interaction terms yet. The model as a whole exhibits a very high R-Squared Adjusted value and claims that at least 54.5% of the variation can be explained by the variables. Also, it is to be noted that all six models state very strong significance values with $p<0.001$.

Since the alleged moderators come with fair but statistically insignificant beta values, Model 2 and 3 are tested with only one of the respective moderators present. Compared with the original model it is striking that Advertised Sustainability as well as Education change in direction when only High Financial Involvement is present as a moderator. However, they remain distinctly insignificant, with the latter even more so compared to the original model. Whereas the beta coefficient for Word Count improves ($\Delta+0.131$) its significance worsens slightly. Next to Education's change in direction, its p-value worsened, too. The negative relationship of Video Count remains but its distinctly worse p-value is striking. Particularly interesting is also the change in significance for References. In Model 1 the variable is close to the significance level of five percent but for Model 2 its p-value is reported at 0.031 and hence marks the third statistically significant variable. This underlines the relevance of the variable, which already had distinctly positive results in simple linear regression. Despite being the only moderator in Model 2, High Financial Involvement severely fades in significance from 0.094 to 0.642. Additionally, the explanatory power of the model decreases by 0.073 in R-Squared Adjusted and 0.577 regarding the F-Statistic.

The procedure of testing only one moderator inside a model is also applied to Model 3. In accordance, High Backers' Experience is added as the single moderator instead of financial involvement. The directions of all variables turn back to those existent in the original model and also the standardized beta coefficients match the original model fairly closely again. A notable exception constitutes the improvement of Word Count, which increases slightly in beta value by 0.063 and demonstrates a much better p-value of 0.476 versus 0.870 albeit still remaining clearly insignificant. The regressor References achieves statistical significance similarly to the second model and discrepancies in coefficients or significance are minor. Once again, the supposedly moderating variable is insignificant despite its fairly high beta coefficient compared to the other moderator tested in Model 2. Overall, Model 3 is more in line with the original model and decreases by only 0.017 in R-Squared Adjusted but instead slightly gains in F-Statistic by 0.178.

After both alleged moderators lack of statistical significance in simple linear regression (cf. Table 9) and also when included simultaneously as well as separately in multiple linear regression equations, the next step is to exclude both as shown in the regression output of Model 4. Again, the three variables of comments, social media and references are statistically significant and their beta coefficients match the second model better than the third or the first, although these strong predictors are rather similar across either model with an alleged moderator. The proximity to Model 2 holds true for the other variables much more, though, with the exception of Word Count. The descriptive elaborateness gains in standardized beta values by 0.120 when High Financial Involvement is included in the model. On the other hand, Education exhibits a delta of +0.162 causing the change from a negative to positive but still insignificant relationship when High Backers' Experience is added. The significance levels of Education are still too irrelevant for any model, however. Similar can be said about the amount of videos when High Backers' Experience is subjoined (Δ+0.091). Due to the fact that in the latter case the p-value actually gets closer to statistical relevance (Model 3: p=0.087 vs. Model 4: p=0.351), one last model is presented with regards to moderators.

When comparing the second and third model against the original as well as the model without alleged moderators, it is striking that Word Count, Video Count and Education are the variables that are the most affected in their statistical results. The variables Word Count and Education are far from significant p-values and the rest of Model 2 is very similar to the model without any supposed moderators. Thus, the variable lacks reasons to be considered a relevant moderator. Video Count still fails the five percent level but at least makes it within the more generous ten percent border when High Backers' Experience is part of the regression equation in Model 3. While not sufficient in itself this outcome is the reason for describing a model that incorporates an interaction term between the potential moderator and Video Count. Before multiplying the variables to get the interaction term, the variables are mean-centered, first. Standardizing variables typically means subtracting the mean and then dividing by the standard deviation. However, this affects the standard deviation, its distribution (e.g. skewness) and the way to interpret the coefficient results. Accordingly, the continuous variable is only centered as this still deals with multicollinearity that otherwise would pose a problem when blending two variables into one. It is done by first computing means for each continuous variable and then subtracting the mean from each observation respectively. Additional manual tests for interaction terms of either supposed moderator reveal no noteworthy results. Controlling aside, Model 5 includes the mean-centered variable of Video Count multiplied by High Backers' Experience. The interaction term shows a strong negative beta coefficient (-0.185) but is statistically insignificant, not even passing the ten percent level. As a consequence, moderator testing finally ends with no statistically significant results discovered and leads to the last model stated in Table 10.

So far the hierarchical regression analysis yielded three variables that came in under an alpha level of 0.05. This is only true for three out of the five models presented, however. Therefore, Model 6 includes solely these variables in order to conclude on this topic. A look at the table manifests the findings thus far. Comments Count - Updates Section - During Campaign, Social Media Advertised and References are all exhibiting p-values below 0.01. Their strong beta coefficients remain existent and the overall model manages an R-Squared Adjusted value of 0.502. Despite not being the absolute highest among all models tested, the result is remarkable considering that the model only includes three variables, which, said differently, account for half of the variability in the dependent variable on their own. An additional note concerns the F-Statistic, which provides the most notable change among all models tested by far. Its value of 18.822 is more than double of any other and illustrates the adequateness of the model. As a consequence, the three independent variables equal the model with the smallest amount of statistically significant predictors.

Table 11

Regression results of central vs. peripheral route

		MODEL 7		MODEL 8	
		β (Std.)	Sign.	β (Std.)	Sign.
IV	1	0.208	0.147	-	-
	2	0.040	0.775	-	-
	3	-	-	0.521	**0.000**
	4	-	-	-0.014	0.888
	5	-	-	0.281	**0.008**
	6	0.235	0.141	-	-
	7	0.080	0.613	-	-
	8	-	-	0.308	**0.004**
MODEL	R^2	0.169		0.531	
	R^2 Adj.	0.101		0.492	
	F	2.484		13.845	
	Sign.	0.056		0.000	

Independent Variables (IV): 1 = Word Count; 2 = Video Count; 3 = Comments Count - Updates Section - During Campaign; 4 = Advertised Sustainability; 5 = Social Platforms Advertised; 6 = Education; 7 = Expertise; 8 = References
Dependent Variable (DV): Amount Of Backers At End Of Campaign (Log-Transformed)

With reference to the dual process theme of this research two additional models are introduced within Table 11. All variables are allocated into the central or peripheral route according to the visualization in Figure 1, with the exclusion of the originally presumed moderators. Model 7 incorporates the four variables of the central route whereas Model 8 integrates the four variables corresponding to the peripheral route. The central route still manages to explain 10.1% (R-Squared Adjusted) with the variables of Word Count and Education exhibiting strong beta values. Despite the lack of statistical significance of any variable, the overall model just marginally falls short with a p-value of 0.056. Nonetheless, alike the model's other numbers also the F-Statistic is the lowest among all models tested and thus offers no surprises. Also Model 8 produces expected results since only the advertising of sustainability is added to the model compared with Model 6. The three previously described very strong predictors are almost identical to Model 6 with deltas of a maximum of 0.002 in standardized beta coefficients and 0.001 in p-values. Advertised Sustainability exhibits no tangible relevance but does cause the model to drop regarding R-Squared Adjusted (Δ-0.026) and F-Statistic (Δ-4.977). It exemplifies that both terms account for the number of regressors in contrast to the insufficient R-Squared value, which still increased by 0.001 compared to Model 6.

In conclusion, the execution of hierarchical regression is demonstrated via eight models. The analysis emphasizes the relevance of three highly-significant predictors, of which all are part of the peripheral route. After the dismissal of moderators, Model 4 constitutes the model with the most independent variables included. Still, the model produces similar enough results with Model 6, which only incorporates the statistically significant predictors. Model 4 appears to be the model of choice as it is the closest to the original research model while providing the second highest F-Statistic values in the original hierarchical regression analysis, ranked right after the smallest model tested (i.e. Model 6). In spite of social sciences' typically low R-Squared values, regression results in this research appear extraordinary high. In order to address concerns on the validity of the results the following subsection discusses robustness. Checks primary concern Model 4 but are extended to all models tested for complementary purpose.

5.3 ROBUSTNESS

The assumptions that linear regression bases on are elaborated in the methodology chapter. Its first presupposition, viz. linearity, is dealt with in section 5.1 already as it is the premise without which any further steps into the regression analysis are questionable. Notwithstanding, it is pointed out that the similarity in the results of Model 4 and Model 6 (see Table 10) indicate that Video Count does not cause complete detriment to the regression despite its lack of linear relationship with the log-transformed dependent variable.

Figure 4

Histogram of standardized residuals of Model 4

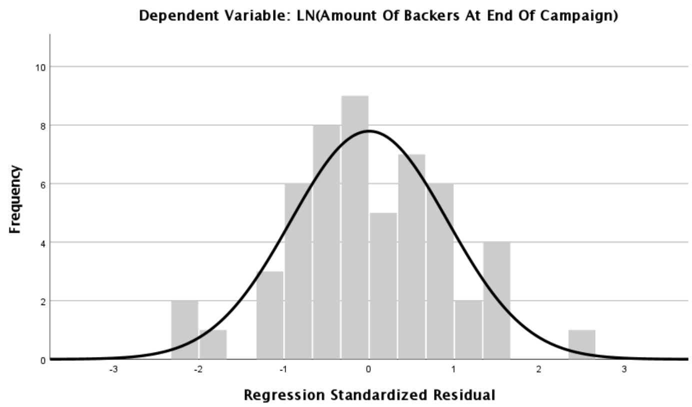
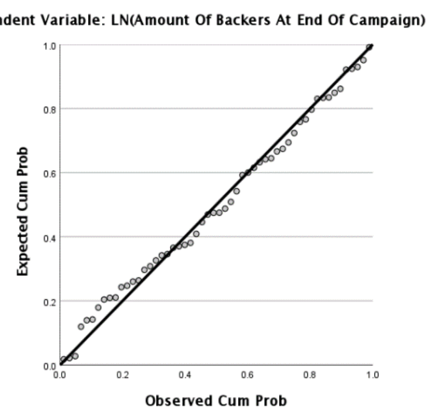


Figure 5

Normal probability plot of standardized residuals of Model 4



Linear regression does not strictly require normal assumption per se, especially when considering the Central Limit Theorem as discussed in the fourth chapter. However, the regression analyses within this paper also emphasizes the investigation regarding statistical significance and hence it is recommended for the condition to be checked. This can be done via two approaches, namely graphically as well as statistically.

A visual inspection of the histogram as well as the normal probability plot of the standardized residuals is a common technique due to its ease. Both are graphed on the left and check the standardized residuals of Model 4 with the log-transformed variable of the amount of backers as the dependent variable. Figure 4 depicts the histogram and Figure 5 follows with a probability plot. The histogram contains the reference line of normal distribution, also known as the bell curve. Although deviations occur above and below the reference line the shape appears roughly normal. Additionally, potential outliers are well within three standard deviations and do not cause enough concern for additional testing. The normal probability plot reinforces the assumption of normality as most of the values are aligned along the 45-degree line. Although one tail differs stronger the overall result is rather linear and signifies no reason for doubt, either.

Nonetheless, visual inspection is based on imprecise decisions. Therefore, the one-sample Kolmogorov-Smirnov test is executed as a non-parametric method to statistically test for the presupposition of normal distribution. Hence, this technique contributes to the visual inspection by providing numerical results via hypothesis testing. The null-hypothesis in a Kolmogorov-Smirnov test is associated with the assumption of normally distributed data; its alpha level is chosen to be the typical five percent. The results for the residuals (p=0.100) as well as predicted values (p=0.077) confirm the visual assessment and are statistically insignificant at p>0.05. Consequently, it can be concluded that the presumption of normal distribution is satisfied.

The last graphical output in this chapter concerns the scatterplot of the residuals. As previously explained, linear regression does not require any individual variable to follow the normal distribution. Notwithstanding, computing the natural log of the Amount Of Backers At Campaign End does in fact change the dependent variable towards being normally distributed, as illustrated in the comparison between Figure 2 and Figure 3. The loss in linear relationship of Video Count with the LN(DV) is sacrificed for the fulfillment of the condition of independence and equal variance. The scatterplot of the standardized predicted values against the standardized residuals before taking the natural log of the regressand in Figure 6 unequivocally reveals a pattern of linear relationship. Residuals are not supposed to allow such clear predictions, though, and thus the regression results would be questionable. However, logarithmic transformation of the amount of backers alleviates the issue substantially. Figure 7 depicts a scatterplot in which the values are rather randomly allocated yet clustered around the middle and around low values of the y-axis. With reference to the assumption of equal variance among the residuals, no distinctly heteroscedastic patterns are visible. The only notable mention concerns two extreme values on the x-axis but they do not resemble the starting point of a stereotypical cone-shaped spread of the values. Hence the assumption of homoscedasticity is argued to be sufficiently satisfied.

Figure 6

Scatterplot of predicted values versus residuals of Model 4 before log-transformation of DV

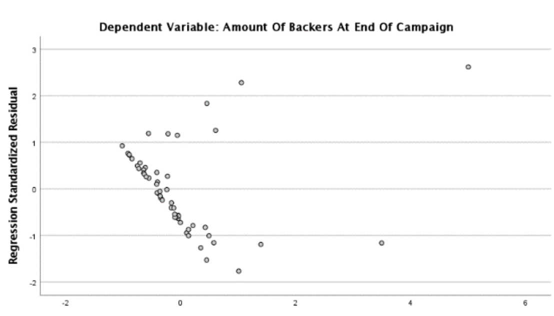
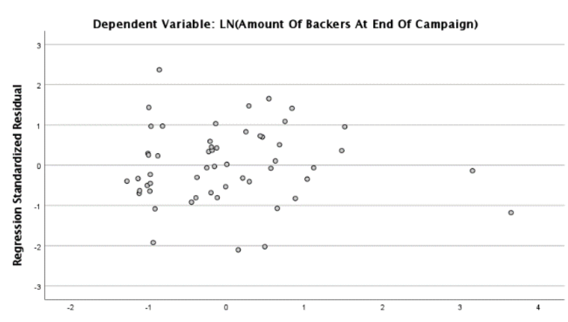


Figure 7

Scatterplot of predicted values versus residuals of Model 4 after log-transformation of DV



Regarding the supposition of independence it is evident that the criterion of randomization is not applicable. Nevertheless, the scatterplot in Figure 7 does not enable any systematic prediction and its random scatter therefore complies with the implication of independent residuals. Concerning the independence between variables the additional tables below extend the checks.

Table 12

Regression results regarding variance inflation factors

	VIF							
IV	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1	1.499	1.465	1.335	1.355	1.320	–	1.177	–
2	1.313	1.305	1.313	1.303	–	–	1.115	–
3	1.618	1.476	1.570	1.456	1.503	1.054	–	1.060
4	1.243	1.172	1.240	1.171	1.152	–	–	1.063
5	1.231	1.128	1.225	1.118	1.143	1.024	–	1.066
6	1.843	1.734	1.806	1.717	1.771	–	1.457	–
7	1.545	1.641	1.508	1.572	1.457	–	1.456	–
8	1.266	1.312	1.258	1.312	1.297	1.076	–	1.084
9	1.326	–	1.255	–	–	–	–	–
10	1.349	1.195	–	–	–	–	–	–
11	–	–	–	–	1.383	–	–	–

Independent Variables (IV): 1 = Word Count; 2 = Video Count; 3 = Comments Count – Updates Section – During Campaign; 4 = Advertised Sustainability;
5 = Social Platforms Advertised; 6 = Education; 7 = Expertise; 8 = References;
9 = High Backers' Experience; 10 = High Financial Involvement; 11 = Interaction: Video Count (Centered) x High Backers' Experience
Dependent Variable (DV): Amount Of Backers At End Of Campaign (Log-Transformed)

The extension from simple to multiple linear regression requires a look at the correlation between the independent variables. The variance inflation factor is utilized to check for multicollinearity. Remarkably, Table 12 reports that all VIF values very close to its lowest possible value of one. The larger the variance inflation factor, the larger the risk of negative effects of multicollinearity. In statistics, the number five as well as ten are often used as threshold to decide upon the presence of multicollinearity. The maximum number within the hierarchical regression constitutes in the value 1.843 and logically is prominent within the model with the most independent variables included. Model 4 reduces the maximum VIF value to 1.717 but the improvement is negligible. Interestingly, though, Model 6 and Model 8 have very good variance inflation factor values ranging between 1.024 and 1.084. This substantiates that the three very strong predictor of Comments Count – Updates Section – During Campaign, Social Platforms Advertised and References are not intercorrelated but are actually uniquely contributing to the predictive power of the model. This is particularly noteworthy since all three variables are categorized as electronic word-of-mouth. Thus, multicollinearity does not pose a threat to the regressions and its assumption is not violated.

Table 13

Regression results regarding Durbin-Watson test

		α = 0.01		α = 0.05	
	d	dL	dU	dL	dU
Model 1	1.461	0.955	1.864	1.110	2.044
Model 2	1.424	0.977	1.805	1.156	1.986
Model 3	1.587	0.977	1.805	1.156	1.986
Model 4	1.445	1.039	1.748	1.201	1.930
Model 5	1.592	1.039	1.748	1.201	1.930
Model 6	1.425	1.245	1.491	1.421	1.674
Model 7	1.218	1.206	1.537	1.378	1.721
Model 8	1.430	1.206	1.537	1.378	1.721

d = Durbin-Watson test stastic; dL = d Lower Bound; dU = d Upper Bound

An additional technique to inspect the independence of the residuals constitutes in the Durbin-Watson test (Durbin & Watson, 1951). Although the test is primarily used for time-series data it still provides insight into correlation between residuals and helps distinguishing whether statistical significance of variables included in the regression are overestimated. Its null-hypothesis is associated with no autocorrelation among the residuals and decision-making predicates on lower and upper bounds of critical values. Based on tables by Savin & White (1977), the bounds for an alpha level of 0.01 as well as 0.05 are illustrated in Table 13. The range of the Durbin-Watson test is between zero and four, with lower values indicating positive and higher values negative autocorrelation. As visible in Table 13 the test statistic for all models lie within the interval of lower and upper bounds. Consequently, the test does not produce conclusive results and, conservatively, the null-hypothesis is not rejected. Therefore, no presence of autocorrelation is detected and the fulfilled assumption of independence persists.

In conclusion, checks for the robustness of the regression results show that the assumptions for multiple linear regression are mostly fulfilled. Hence, the correctness of the statistical output is endorsed and final conclusions can be drawn as to be presented in the next chapter.

6. DISCUSSION

The final chapter synthesizes the most relevant theoretical and empirical findings. A conclusion is presented in text form as well as a final figure based on the research model. In addition, the limitations of the paper are addressed and opportunities for future research are pointed out.

6.1 CONCLUSION

Throughout the course of this paper it has been established that electronic word-of-mouth and crowdfunding share contextual (e.g. Internet) as well as internal (e.g. social components) aspects that manifest the connection between them. With the help of signaling theory it has been explained that asymmetries in information and expertise may be resolved with the help of social information and is argued as a rationale for investigating its applicability in the context of sustainable reward-based crowdfunding, which can be seen as online purchasing. Since sustainable attributes are more difficult to measure and evaluate (e.g. Parris & Kates, 2003; Wehnert et al., 2019), the bridging of informational disadvantage accentuates in its importance considerably. The credibility of the information and its source has been discussed as relevant and is also related to trust (Luo et al., 2014), which Liang et al. (2019) found to positively influence the decision to fund. The authors also discover that the relationship is moderated by product category and that social and economic projects are similar in this regard, which may support the applicability of crowdfunding in the sustainable setting. Considering the nascent state of research into sustainability crowdfunding, this study appears of particular relevance. Accordingly, the research question of this study includes multiple facets with the aim to contribute to different streams of research. The focus of the question circles around the role of electronic word-of-mouth regarding critical success factors for sustainable crowdfunding campaigns. Thus, the following concludes on the hypothesized signals of campaign performance.

With reference to Word Count (H1a), the empirical results are fairly surprising. Opposite to many studies, the length of the campaign description only holds true for its hypothesized positive effect on backers' funding intention when tested individually but fails to do so in every model tested. Racherla and Friske (2012) discovered a similar contradiction in their empirical research as the descriptive elaborateness of an eWOM message is not confirmed as a positive contributor despite previous studies' stating the opposite. The authors note that it may be reasoned with the audience falling back to contextual cues when the amount of data becomes too large. This is similar to Rogers (2003), who delineates that more information can also lead to dissonance. Additionally, an increasing amount of information may also result in an excessive need of resources (e.g. time and cognitive efforts) to process and hence be discarded (Allison et al., 2017; Petty & Cacioppo, 1986; Wehnert et al., 2019). This may then be particularly true when less effortful information is available. The reason for this thought lies in the different results between the models. Tested individually, Word Count shows a strong beta value with an alpha level of less than three percent. Yet in every other alternative modeled in multiple regression the variable cannot reach statistical significance at all. With this also being true in the model with only the central route present (i.e. Model 7), it weakens the reasoning but the strong beta is still noticeable and much closer to the individual test.

Moreover, the data points in this variable stand out for their spread in absolute values. Since a log-transformation of the variable did not result in remarkable differences as previously mentioned, it retains high absolute values as shown by its standard deviation of ca. 778 words. Its coefficient of variation is approximately 0.54 and thus poses no concern. Instead, it indicates that ca. 68% of the sample ranges between ca. 652 to ca. 2208 words and hence creators appear to not follow a shared, generally accepted rule in their decision regarding the length of the campaign description. The contradiction is further visible with a look into the dataset. Despite its skewness to the right and a maximum of ca. 3452 words, also the lowest number (i.e. ca. 187 words) is fairly strong in the opposite direction. Interestingly, both cases are examples that show support for the hypothesis with the short campaign description failing to reach funding and the longer one being the most successful campaign within the sample. Accordingly, the hypothesis shall not be dismissed without the concomitant suggestion of retesting it with a larger sample to see if these positive indications are simply due to extremity or chance, or whether the conclusion indeed changes with the help of more data points gathered that also improve generalizability.

The second indicator of project quality tested consists in the presence of audiovisual content (H1b). The amount of videos depicted on a campaign page do not show the hypothesized relation. Instead, all models that include both central and peripheral cues yield a negative relationship with backers' decision to invest. Once the peripheral route is excluded, however, the effect turns positive. Nonetheless, the outcome is rather negligible as no test educed statistical relevance. It is noteworthy, however, that more experienced backers appear to respond negatively to audiovisual cues yet the interaction term does not substantiate this sufficiently. Lagazio and Querci (2018) also negate the positive contribution videos make on crowdfunding performance. The authors do not use their empirical results as counter evidence, though, but draw the conclusion that the influence of videos is not able to systematically persuade investors, instead. Since literature on crowdfunding primarily advocates in support of implementing videos, even in the context of sustainability (Bento et al., 2019b), it should therefore still be reckoned as a surprising finding. It remains questionable though as to how reliable this specific variable is in the hierarchical regression analysis considering the change in relationship after log-transforming the dependent variable (cf. Table 8).

In addition, the videos were gathered with exclusive focus on the quantitative character. Dichotomous and metric measurements were collected and tested that consider presence, amount of videos as well as their lengths in seconds as another control variable. This type of data does not provide any insight on the qualitative aspects though and hence may fall short in explaining the direction of the variable's influence. Literature on electronic word-of-mouth attests differences in effects to examples like rhetorical strategies (King et al., 2014), valence (Chevalier & Mayzlin, 2006) and argument quality (Cheung & Thadani, 2012). Similarly, crowdfunding research notes sentiment and linguistic style as examples for written content (Parhankangas & Remko, 2017) and it is even unknown whether a video depicts an animated rendering or an actual prototype (Olanrewaju et al., 2020). Thus, it is reasonable to consider that qualitative factors could influence the perception of audiovisual cues, such as the professionalism with which the video is produced, the sidedness and tone of the story, color scheme, the message itself or who is performing (e.g. creator, business partners, consumers, key opinion leaders). Consequently, future studies could add potentially novel value by investigating videos on campaigns from a qualitative perspective. The qualitative view is also relevant regarding written content (H1a) whereas it received some attention in literature already and is not as novel – e.g. spelling errors (Mollick, 2014; Wessel et al., 2016) and multiple language-related considerations studied by Parhankangas and Remko (2017). Analysis beyond the quantitative nature is however not feasible for this study and results in a common limitation.

The mixed results regarding hypothesized indicators of project quality continue with respect to the creator of the campaign. While simple regression discovers strong and significant values in support of H2a, the actual results from all tested models indicates insufficient conformity regarding Education's beta values – also no model bears statistical significance for it. Interestingly, creator's educational disclosure is similar to descriptive elaborateness in so far that Model 7 (i.e. central route only) comes closer to the very strong results from individual testing. In equity crowdfunding, backers are assumed to be more comparable to traditional investors, who diligently assess an entrepreneur during their decision-making (Ahlers et al., 2015; Allison et al., 2017). Backers in reward-based crowdfunding are perceived as less knowledgeable and the typical pre-order transactions involve lower financial risk (Belleflamme et al., 2014). Although backers with more experience appear to value information about the creator's

Table 14

Overview of supported hypotheses

HYP.	VARIABLE	SUPPORT
H1a	Descr. Elaborat.	No
H1b	Videos	No
H2a	E. Education	No
H2b	E. Experience	No
H3a	Comments	Yes
H3b	Social Plat. Adv.	Yes
H3c	References	Yes
H4	Sustain. Orient.	No
H5	Fin. Involv.	No
H6	B. Experience	No

education more, the results are insufficient to conclude a systematic benefit of disclosing the educational background and thereby H2a is dismissed.

The observation is similar regarding prior entrepreneurial experience (H2b). Falling just short of significance ($p = 0.055$) when tested separately, the p-values drop when modeled. The variable remains stable across models except when only central cues are present (i.e. Model 7). Overall, the almost consistently high beta values may be indicative of its positive influence but cannot manifest the hypothesized relationship due to the lack of statistical significance. However, it should be noted again that prior experience was measured by its advertising and not by counting previous campaigns and that both exhibit shortcomings.

Before moving to the hypotheses concerning the peripheral route, it is noteworthy that electronic word-of-mouth may also offer potential for entrepreneurs with regards to disclosing the professional network to the audience. However, the incorporation into the campaign is barely existent in the sample. Only two out of the 50 campaigns advertise their professional social media account, namely in both cases LinkedIn. While channels that are used for private purposes are said to exhibit higher innovative user-generated content compared to networks intended for professional use (Candi et al., 2018), the inclusion of the professional network may serve another purpose. Instead, it may supply additional inferences that help regarding the creator's educational and professional qualifications but also extend to the social capital that is related to the entrepreneur's network. The latter is suggested by Mollick (2014) in the case of Facebook and is also discussed by Wang and Yang (2019), as previously mentioned. Thus, backers may get a better grasp of internal and external resources available that play a role in the entrepreneur's ability (Wang & Yang, 2019). Shneor and Munim (2019) perceive the utilization of social capital in form of the entrepreneur's network as a critical success factor, even. Future research may therefore dive into the impact of professional networks on sustainability crowdfunding and guide creators into improving their strategic use of social networking and therewith possibly affect the outcome of variables such as education and experience.

Next, the peripheral cues are addressed. Electronic word-of-mouth has received prioritized attention in this study and the empirical results underline the rationale behind it. Comments (H3a) that are posted on the update section during the run of a campaign dominate the statistical results in both simple and multiple regression. Being the variable with the highest explanatory power (see simple regression) and consistently best beta- and p-values (see multiple regression), H3a is fully supported. It also is the only independent variable with a high coefficient of variation (i.e. ca. 2.45) and hence its standard deviation is much higher than its mean, reflecting a large spread in the observations. With reference to descriptive statistics and visualizations it can be ascribed to the well-performing campaigns as those possess a strongly increased volume of comments. Whereas it remains opaque how much this is due to underlying relations with the number of updates or their like count (see section 5.2), this finding is remarkably strong and consistent with previous literature (Courtney et al, 2016; Kim et al., 2017; Wang et al.,2017). Moreover, the predictive strength of comments is confirmed by Cho and Kim (2017) for a western as well as Asian background and therefore embraces the global theme of the crowdfunding phenomenon – interestingly, the same cannot be said for the number of updates since the study only found it significant in the former. In accordance, the communicative participation of consumers within the campaign page is critical to the campaign performance.

With regards to the advertising of social media (H3b), the pattern in the empirical results is almost identical to comments. While the numbers are not as strong they are as consistent across models. Consequently, the hypothesis (H3b) is supported. Promoting the engagement in social media with regards to the campaign is argued as a proxy of actual activity on social networking sites and thence external of the crowdfunding platform. The binary coding of this variable is constrained to a superficial layer and its meaning is to be treated with caution. Nonetheless, existing literature also points out the relevance of social media metrics so this paper goes along with studies such as Lagazio and Querci (2018), Mollick (2014) and Olanrewaju et al. (2020).

References (H3c) that are present on the campaign page are the final form of electronic word-of-mouth addressed in a hypothesis and frame external, third-party content implemented into the campaign description. The variable features strong explanatory power in individual testing and offers high beta values in all yet slightly falls short of statistical relevance in two models. Model 1 possibly dilutes the regression with too many variables and Model 5 lacks of pertinence. Hence, also the hypothesized influence of References (H3c) is supported. This finding is consistent with Bi et al (2017) and leads to the following conclusion. The empirical results on electronic word-of-mouth are in line with the larger eWOM research as well as crowdfunding in specific. The twofold character of (im-)material support claimed by Shneor and Munim (2019) is also present in this study. Therefore, consumers' engagement is of essence and the availability of information from those and other third-parties (e.g. media) is of relevance.

As an anecdote, a complimentary analysis of the gathered social media data is given. When plotting the collected data points against the natural log of backers at the end of a campaign, it seems that successful projects have favorable Facebook and Instagram statistics. Such outcome is in line with literature emphasizing Facebook's role (e.g. Jiménez & Mendoza, 2013). When keeping in mind that the campaigns in question were concluded at different points in time it means that successful campaigns vary in their advantage of establishing an audience over time and do not offer any reliable information regarding causal relationships with the actual campaign. Consequently, further analysis is not included in this paper. Nevertheless, even more variables are inspected in an attempt to verify other expected behavior when considering data after the campaign's end. An example can be found in the number of updates posted by the campaign creator. Modelling only the independent variable of update count against the natural log of the amount of backers at the end of a campaign demonstrates a substantial improvement in R-Squared of 0.320 (linear) or 0.245 (quadratic) from the amount of updates published at campaign end versus total. This may be explained by the simple logic that successful campaigns exhibit, both, more time and reason to share more updates with the community. Creators may share the progress of development, production and shipping or give backers more information regarding the product choices after finalizing color options, for example. Whereas this bears no further value regarding the statistical execution, which is limited to the time period within the campaign's original runtime, the vast data collection and the only exemplified presentation of it aids to understanding the rationale behind choices made.

With reference to social and environmental motives, the findings are fairly clear. Advertising sustainable attributes in the way measured does not provide any statistically relevant impact. The variable's consistently low beta values change in direction from positive to negative in three models yet this holds no meaning as p-values numerically almost reach one. Even in an individual view (see simple regression) the variable fails to explain 'any' variance (R^2 Adj. = 0.000) and therefore H4 is not supported. The result basically stands in contradiction to those of Calic and Mosakowski (2016), who find support for technology products but not for another category. The authors do mark though that backers' characteristics (e.g. values) and also the backers themselves may change over time. Consequently, additional research with a longitudinal design may facilitate the comprehension and applicability of this rationale.

Moderators of motivation (H5a, H5b) and ability (H6a, H6b) pose the last hypotheses to mention. Contrary to the three other papers that study signals in reward-based crowdfunding with the help of the Elaboration Likelihood Model, namely Allison et al. (2017), Liang et al. (2019) and Wang and Yang (2019), moderators barely provide reason for inclusion. Neither the backers' prior crowdfunding experience (i.e. first-time backers ratio) nor the financial requirements (i.e. risk expressed in pricing) offer statistically significant insights into why consumers may choose one route over the other. Incorporating one or the other variable does not affect the outcome of the peripheral route and causes some but non-significant effect on the central route with Word Count, Video Count and Education being altered the most. Hence, their impact is rather negligible.

Whereas the approach of approximating backers' knowledge is consistent with Allison et al. (2017) it may still be more proper to inquire input from consumers themselves (e.g. with the help of a questionnaire) to get a better grasp of their expertise about the offering, similar to Wang and Yang (2019). A follow-up study could therefore address this subject. Also, a possibly more important consideration refers to the category analyzed. Utilitarian products are distinct from those with hedonic character. In addition, the context of sustainability adds another layer of specificity. Thus, additional and preferably larger samples could be taken for sustainable campaigns from the same as well as other categories and illuminate on possible discrepancies.

According to King et al. (1994), a research question is advised to address a matter of relevance in the search to generate additional insight into the respective phenomenon and to add to existing literature and knowledge. The conclusion ends by elaborating on it in the following paragraphs. Altogether, it is noteworthy that no variables in this study reach statistical significance across any model other than those of electronic word-of-mouth. Despite the lack of support towards the respective hypotheses, all non-eWOM variables, except for sustainability advertising, feature beta values that can be perceived as indicatory and at least weakly imply partial consistency with existing knowledge. However, the lack of statistical significance sets electronic word-of-mouth apart as the only distinct contributor. The three variables concerning eWOM are able to explain half (Model 6: R^2 Adj. = 0.502) of the variation in the modeled campaign performance, which signifies a remarkable result in the sphere of social science.

A possible explanation for the superior influence of electronic word-of-mouth on the decision-making may be exactly one of the reasons for undertaking this study. The severe asymmetry in information and expertise may represent a barrier for consumers to independently judge the intangible offering and is further accentuated in the context of sustainability. Accordingly, signals from third-parties, including fellow consumers, may help overcoming the difficulties in the decision-making process by representing credible sources of information for otherwise undiscernible characteristics. Since Wehnert et al. (2019) claim to be the only paper investigating the credibility of sustainability signals and do so in a different approach post-campaign, this study contributes through the analysis of factors during the campaign. The implications for entrepreneurs are rather similar, though. It appears critical for creators to consider alternative approaches to the credibility of their communication strategy (Wehnert et al., 2019) and this paper provides empirical suggestions for eWOM to execute that role, which addresses the question by Petruzzelli et al. (2019) regarding how entrepreneurs shall manage the sustainability aspect in their campaigns. The interactivity and transcending abilities of social media may also provide an adequate instrument to extent the entrepreneurial marketing efforts (Fink et al., 2020).

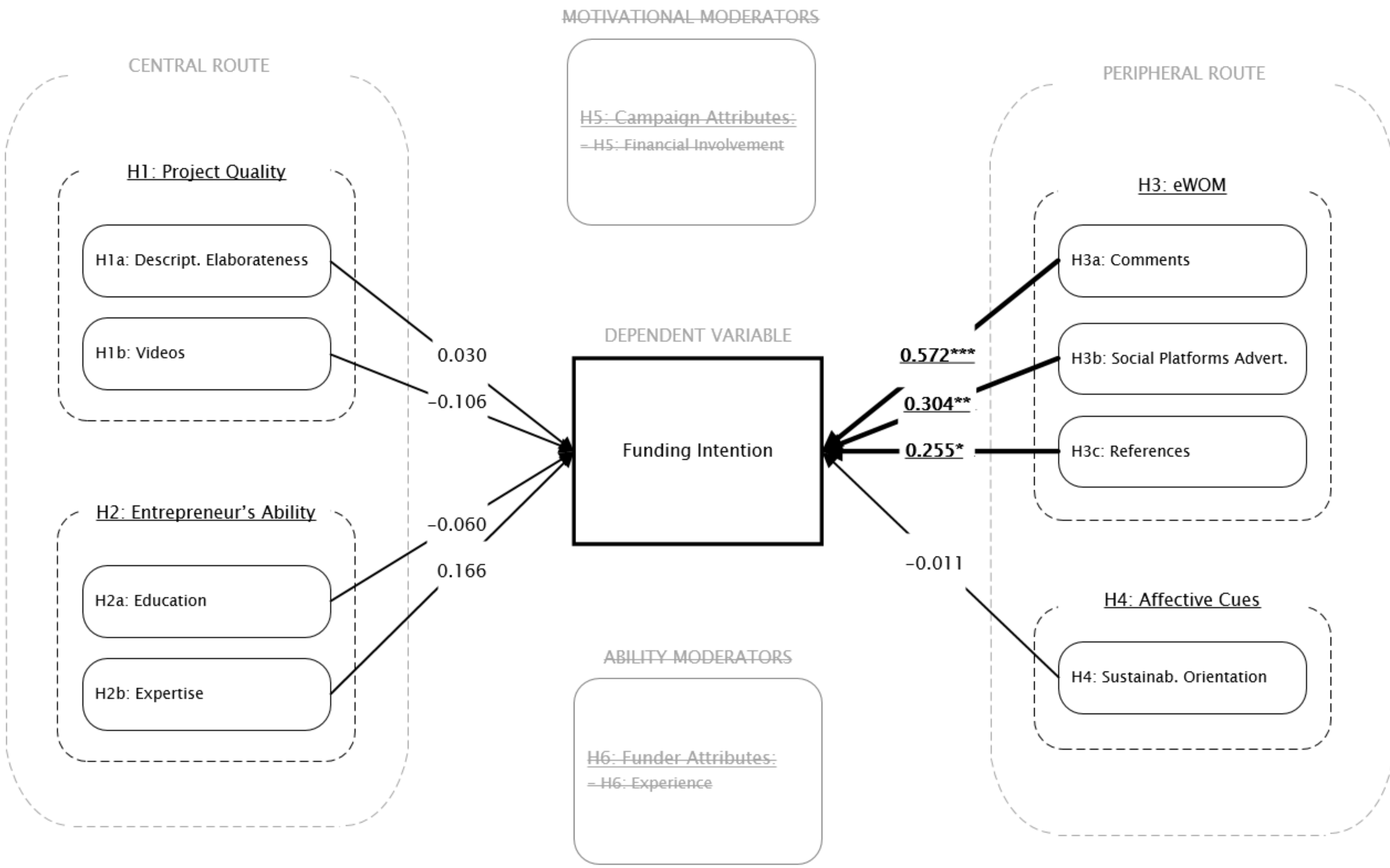
Further, this paper can be perceived as a more comprehensive extension of the rare study from Bi et al. (2017). Therefore, this research may constitute the first to analyze the role of eWOM in the decision-making process of sustainable entrepreneurship through the lens of ELM and signaling. Whereas signaling theory facilitates the basic understanding of the topic (e.g. asymmetry), the Elaboration Likelihood Model provides additional insight. The applicability of the latter is argued to hold as it explains differences between signals with its dual-process character in what is argued a consumer purchase decision-making, yet the empirical findings cannot corroborate its moderating aspects.

In the end, crowdfunding can be viewed as an instrument that enables entrepreneurial endeavors of any scale and that facilitates innovators to cooperate with unknown peers (i.e. co-creation), explore market potential and advertise their offering, all while contributing to economic and societal development (Bellelfamme et al., 2014; Wang & Yang, 2019). In other words, reward-based crowdfunding represents a potential alternative to conventional financing and innovative commercialization in the context of sustainability (Bento et al., 2019b; Petruzzelli et al., 2019). An actual superiority of sustainability per se cannot be unequivocally concluded with the empirical results demonstrated since such orientation (H4) does not provide statistical relevance in the sampled campaigns in the way the variable was computed. On the other hand, it is notable that the success rate of sustainable technology products in the sample (i.e. 34%) is just below Kickstarter's overall rate (i.e. ca. 38%) yet considerably higher than the technology category (i.e. ca. 20%) the sample is derived from, thereby elevating the category from its otherwise least successful position on the platform (see sections 1.2, 2.3, 5.1). In other words, there is partial data in the sample that suggests sustainability to offer higher chances of success. The criteria set for H4 are thus of question and require more critical reflection concerning the referenced approach of Calic an Mosakowski (2016). This may also go hand in hand with criticism on the lack of specificity of sustainable parameters (see section 2.3) and their partially unverifiable nature (see section 3.1).

Nonetheless, sustainability is considered a critical constituent in successful businesses (Shepherd & Patzelt, 2011) and its advantages in crowdfunding are attested in other empirical studies (e.g. Calic & Mosakowski, 2016). Bento et al. (2019b) delineate that crowdfunded sustainability projects are in fact achieving a 70% survival rate after the first year of business, countering the notion that sustainability orientation appears less attractive than regular commercial endeavors (e.g. Petruzzelli et al., 2019). The benefits to social causes are additional indications as exemplified for female entrepreneurship in section 2.3. As a consequence, it would be interesting to see whether investigating a larger sample gives more credit to either side of the story. Also, inconclusive and contradictory findings are not unsurprising for an emerging field of research and should only encourage further exploration of the topics – not at last since sustainable entrepreneurship seeks for pivotal resolutions of issues of global magnitude. After all, regardless of whether sustainable orientation constitutes a competitive advantage, this study is in alignment with literature in that crowdfunding plays a relevant part in sustainable entrepreneurship and this paper adds that electronic word-of-mouth follows suit.

Figure 8

Research model with results from Model 4



Note: * p < 0.05, ** p < 0.01, ***p < 0.001

6.2 LIMITATIONS

As with every research it is of importance to address shortcomings and suggest areas of future research. The first constraint of this study is that it is not executing a strictly experimental design but involves collecting data from a public website. Accordingly, the critical condition of proper randomization could not be met for this study since non-probabilistic sampling is employed. In addition, the data was collected post-campaign at a single interval. Thus, it needs to be kept in mind that the gathered information is not a perfect and equally fair representation of the sample itself and that further discrepancies may exist due to the differences in length that campaigns had from their respective end date to collection date. As a consequence, conclusions should be treated with caution and are not infallibly generalizable to the population the sample was taken from, namely Kickstarter backers at large.

In addition, the ability to generalize the findings is also restricted by sampling from only that specific source. Whereas Kickstarter constitutes the largest reward-based crowdfunding platform in the United States (Kuppuswamy & Bayus, 2017), it may not be representative of the global phenomenon as a whole. Already US-based competitors such as Indiegogo have a different positioning (cf. section 1.2) and the results may therefore vary – especially when considering the diverse backgrounds of social participants (Olanrewaju et al., 2020). The discrepancies may also widen with reference to the impact of culture (cf. sections 1.2 and 6.1), which Luo et al. (2014) argue to be a relevant moderator across research domains, and is also known to influence purchasing behavior (King et al., 2014). According to Terán-Yépez et al. (2020), four out of the five countries (1st: UK; 2nd: DE; 4th: NL; 5th: ES) that generate the most research articles on sustainable entrepreneurship on Scopus in the time between 2002 to 2018 come from Europe. Despite the Western orientation, the European continent in itself is far from a unified civilization as can be analyzed through Hofstede's (2011) six cultural dimensions. The geographical differences alone can already serve as a simplistic inference and also imply potential disparities in the legislative framework, such as the US' leading role in regulating equity crowdfunding, for instance.

As previously explained, cultural divergence may particularly be of importance the farther the opposite scales. Luo et al. (2014) exemplify this in the domain of eWOM as their study applies the Elaboration Likelihood Model with the moderator of individualism/collectivism. They discover that those that rank higher on individualism are more likely to appraise information credibility based on their own thoughts, whereas those on the collectivist side are more likely to utilize inferences from peers. Similarly, Cho and Kim (2017) disclose cultural differences comparing an Asian (i.e. Korea) versus a Western (i.e. US) background and confirm the individualism/collectivism orientation, for example. Also, the authors state that the sufficiency of available information is an essential factor in crowdfunding success, which may serve as support for the rationale behind the conclusion in the subchapter above.

Moreover, the search term on Kickstarter was intentionally constrained to “sustainability” or “sustainable” to unambiguously analyze only campaigns that specifically advertise the idea of sustainable entrepreneurship. With reference to the study of Bento et al. (2019a), it appears possible to extend the search to include alternative terms and to thereby also enlarge the sample size further. Since increasing the amount of campaigns collected and particularly the added steps of meticulously reviewing each campaign to verify its relevance in sustainable entrepreneurship goes beyond the scale of study, it remains subject for future research.

With reference to the data collection it is also relevant to mention that it required some subjective criteria to be integrated. When looking at the original research model (cf. Figure 1) it is the case for word count and the moderating variables, namely financial involvement and backers’ experience (cf. section 4.2). As explained, creators can use stylistic means to adapt their campaign description and hence a subjective way of standardizing the amount of words was employed and appears to be ignored in previous research (e.g. Bi et al., 2017; Lagazio & Querci, 2018). The subchapter also details that deriving the two moderators involves own decision-making by computing these from other variables. However, when assuming legitimacy in the way the variables’ design follows existing, similar research (i.e. Allison et al., 2017) and considering the fact that the final model does not include moderators, it leaves only descriptive elaborateness as a potential issue. In chapter 4.2, it is argued for it to be of lesser concern though as shown with the inclusion and calculation of dummy variables and their comparison to the adjusted Word Count- yet it is something to be aware of and means that the research cannot be free of bias.

Furthermore, the outcomes of the algorithm-enhanced stepwise regression indicate strong support for the variables concerning the updates section of a campaign page. Thoughts on multicollinearity and the intent of maintaining the original research model was corroborated with remarkable results in simple linear regression of the comments count. The dismissal of the other two variables for this paper does not translate into their irrelevance. As a consequence, these variables remain a topic of interest that may be further investigated in future research.

Next, illegitimate behavior in the online realm is a problematic matter, see subchapter 1.2, 2.2 and 2.3 for reference. Thence, it appears appropriate to address the potentiality of fraudulent behavior within this study. The baseline of legitimacy starts with the entrepreneur’s motive behind the crowdfunding campaign itself. As previously mentioned, the legal framework around crowdfunding varies strongly and therefore customers are required to ‘deposit’ some goodwill when engaging with a project. Despite implying good faith in the entrepreneurs and expecting them to honor their commitment towards delivering the advertised quality of goods, creators may still artificially overstate campaign information. In other words, signals may not be accurate and instead increase the information asymmetry – whether known to the customer or not. Considering the strong statistical results for eWOM and its related discussion in literature, attention is focused on the three respective variables in this study.

As Wessel et al. (2016) pointed out, crowdfunding is subjected to manipulation of quantitative social information. Although the Facebook Like button is no longer present on the campaign page itself, its relevance may not vanish. 19 (38%) of the 50 projects explicitly advertise their social media accounts and serve as evidence that social media plays a role in the sample collected and possibly in sustainable entrepreneurship at large. Its function as a proxy reflects ample opportunities for entrepreneurs to manipulate signals spread through the digital sphere. This includes both qualitative and quantitative data, such as fake discussions or the overstatement of counts (e.g. followers, likes).

Similarly, electronic word-of-mouth can be integrated into the original campaign format in the form of referenced third-parties. Among the 50 campaigns of the sample, exactly half (50%) featured quotations of external sources. Examples of information that may be altered within the gathered campaigns comprise of press coverage and reviews of pre-release versions. These can occur in the form of audiovisual or textual cues and require critical analysis either way. Apart from possible biases through favorable selection of third-parties (e.g. preferred key opinion leaders) and mutually beneficial relationship (e.g. financial incentive), it is possible for creators to generate fake information in their entirety themselves. In fact, within the data collection process, a few campaigns stood out with suspicious YouTube reviews that may exemplify bias, or stock portrait photos along dubious external comments that are integrated into the campaign description, which on the other hand equals a potential example of fake information. Whereas the few obvious projects that raised notable doubt were discarded and not incorporated into the sample, the included campaigns may not be free from deceitful practices. Guidelines to identifying such illegitimate behavior in electronic word-of-mouth and crowdfunding may provide a framework to deal with the issues and help the understanding of the phenomena. Also, maybe technological advancement (e.g. artificial intelligence, algorithms) could support these endeavors, in particular in the process of detection.

The third variable embodying electronic word-of-mouth in this study consists in the comments posted on campaign updates. However, crowdfunding platforms like Kickstarter established mechanisms to restrict entrepreneurs in their ability to artificially boost their campaigns, which also comprises financial performance, too (Mollick, 2014). Since only backers are eligible to contribute to the campaign page by comments or likes, entrepreneurs indeed face restrictions in their capabilities because for a backer to create fake accounts, it takes not only fake personal data but also billing credentials – and in case of a successful campaign also an actual monetary transaction. On the other hand, such procedure does not guarantee to work and considering the room for improvements in terms of transparency and engagement on the side of Kickstarter, manipulation remains a concern. Correspondingly, Mollick (2014) advises institutional actors (incl. crowdfunding platform) to support creator's in their planning and goal-setting and emphasizes the importance of signals.

A final recommendation for future research rounds off this chapter as follows. In essence, electronic word-of-mouth and crowdfunding are strongly interconnected phenomena and base on the engagement of a virtually unlimited, heterogeneous group of peers. Considering the substantial potential that can be drawn from the individuals' diverse backgrounds that remains partly unused, it may be of great value to explore their contribution with the help of theories like social capital (Burt, 1997; Adler & Kwon, 2002) in the context of sustainability. The dilemmas that sustainability entrepreneurship addresses are typically evident on a global scale and encompass complex efforts to solve issues in unprecedented ways. The ability of the two phenomena to tap into the expertise of a motivated workforce and democratize the processes involved in the development of innovative solutions may therefore pose a unique opportunity. Research into the role of electronic word-of-mouth in the co-creation of sustainable crowdfunding, e.g. from a social capital view, may therefore contribute to the comprehension of these highly related concepts and would add not only to the findings of this paper but also to the thriving academic field.

APPENDIX

I. PRELIMINARY RESEARCH OVERVIEW

Table 15

Non-exhaustive overview of theories utilized throughout eWOM and crowdfunding research

THEORETICAL LENSES	FUNDAMENTAL LITERATURE EXAMPLES	RELEVANT LITERATURE EXAMPLES
Ability-Motivation-Opportunity (AMO) Theory	MacInnis & Jaworski, 1989	Gruen et al., 2005
Affective Events Theory	Weiss & Cropanzano, 1996	Davis et al., 2016
Agency Theory	Jensen & Meckling, 1976	Valančienė & Jegelevičiūtė, 2014
Altruism Theory	Andreoni, 1990	Burtch et al., 2013; Cheung & Lee, 2012; Lagazio & Querci, 2018
Attribution Theory	Heider, 1958	Cheung & Thadani, 2012; Dou et al., 2012; Lagazio & Querci, 2018
Cognitive Fit Theory	Vessey, 1991	Park & Kim, 2008
Consumer Trust in E-Commerce	Chen & Dhillon, 2003	Beldad et al., 2010; Oliveira et al., 2017
Contract Theory	Hart & Holström, 1987	Lagazio & Querci, 2018
Commitment-Trust Theory	Morgan & Hunt, 1994	Zhao et al., 2017
Critical Mass Theory	Oliver, Marwell & Teixeira, 1985	Chen et al., 2012
Cultural Dimensions Theory	Hofstede, 2011	Cho & Kim, 2017; Luo et al., 2014; Zheng et al., 2014
Dual-Process Theory	Deutsch & Gerard, 1955, Evans, 1984	See ELM and HSM
Diffusion of Innovation Theory	Rogers, 2003	Stanko & Henard, 2017
Dynamic Capabilities Theory	Teece, Pisano & Shuen, 1997	Fehrer & Nenonen, 2020
Effectuation Theory	Sarasvathy, 2001; Perry, Chandler & Markova, 2012	Fischer & Reuber, 2011
Elaboration Likelihood Model (ELM)	Petty & Cacioppo, 1986	Allison et al., 2017; Bi et al., 2016; Cheung & Thadani, 2012; Liang et al., 2019; Luo et al., 2014; Wang & Yang, 2019

THEORETICAL LENSES	FUNDAMENTAL LITERATURE EXAMPLES	RELEVANT LITERATURE EXAMPLES
Entrepreneurial Orientation (EO)	Covin & Slevin, 1989	Sahaym et al., 2019
Equity Theory	Adams, 1963; Oliver & Swan, 1989	Hennig-Thurau et al., 2004
Expectancy Theory	Vroom, 1964	Bretschneider & Leimeister, 2017; Kuppuswamy & Bayus, 2017
Expectation and (Dis-)Confirmation Theory (EDT/ECT)	Oliver, 1977, 1980	Chen, Yen & Hwang, 2012
Goal-Setting Theory	Locke, 1968	Kuppuswamy & Bayus, 2017; Lagazio & Querci, 2018
Herding Theory	Banerjee, 1992; Bikhchandani, Hirshleifer & Welch, 1997	Colombo et al., 2015; Huang & Chen, 2006; Zaggl & Block, 2019; Zvilichovsky et al. (2018)
Heuristic-Systematic Model (HSM)	Chaiken, 1980	Baber et al., 2016; Gupta & Harris, 2010; Zhang et al., 2014
Incentive Theory	Hockenbury & Hockenbury, 2003	Bretschneider & Leimeister, 2017
Information Adoption Model (IAM)	Watts Sussman & Schneier Siegal, 2003	Gunawan & Huarng, 2015
Information Integration Model	Anderson, 1981	Fink et al., 2020
Information Processing Theory	Bettmann & Whan Park, 1980	King et al., 2014
Input-Process-Output (IPO) Model	Bushnell, 1990	Chan & Ngai, 2011
Institutional Theory	Meyer & Rowan, 1977; Rogers, 2003	Hinings et al., 2018
Knowledge-Based View (KBV) Theory	Grant, 1996	Candi et al., 2018; Stanko & Henard, 2017
Language Expectancy Theory (LET)	Bowers, 1963; Burgoon & Miller, 1985	Anglin et al., 2018; Parhankangas & Renko, 2017; Wu et al., 2017
Media Synchronicity Theory	Dennis, Fuller & Valacich, 2008	Wang et al., 2017
Multi-Level Perspective (MLP)	Genus & Coles, 2008	Testa et al., 2019
Regulatory Focus Theory	Higgings, 1997	Zhao et al., 2017
Resource-Based View (RBV) Of The Firm	Barney, 1991; Grant, 1991; Wernerfelt, 1984	Van Rijnsoever et al., 2017

THEORETICAL LENSES	FUNDAMENTAL LITERATURE EXAMPLES	RELEVANT LITERATURE EXAMPLES
Self-Determination Theory	Deci & Ryan, 1985; Ryan & Deci, 2000	Ryu & Kim, 2016
Self-Representation Theory	Schlenker & Leary, 1985	Bretschneider & Leimeister, 2017; Shneor & Munim, 2019
Signaling Theory	Ross, 1977; Spence, 1973	Aggarwal et al., 2012; Ahlers et al., 2015; Bi et al., 2017; Kunz et al., 2017; Wehnert et al., 2019; Wessel et al., (2016)
Social Capital Theory	Burt, 1997; Adler & Kwon, 2002	Colombo et al., 2015; Kang et al., 2017; Zheng et al., 2014
Social Cognitive Theory	Bandura, 2001; Miller & Dollard, 1941	Cheung & Lee, 2012
Social Comparison Theory	Festinger, 1954	Bretschneider & Leimeister, 2017
Social Exchange Theory	Homans, 1958; Füller, 2010	Brem et al., 2017; Cheung & Lee, 2012; Zhao et al., 2017
Social Identity Theory	Tajfel & Turner, 1979	Cheung & Lee, 2012; Forman et al., 2008; Kromidha & Robson, 2016; Lagazio & Querci, 2018
Social Network Theory	Granovetter, 1973	Kietzmann et al., (2001)
Social Presence Theory	Short, Williams & Christie, 1976; Gunawardena & Zittle, 1997	Cheung & Thadani, 2012
Stakeholder-Based View Of The Firm	Freeman, 1984	Valančienė & Jegelevičiūtė, 2014
Swift Guanxi	Ou, Pavlou & Davison, 2014	Wang et al., 2017
Technology Acceptance Model (TAM)	Davis, 1989; Davis, Bagozzi, Warshaw, 1989	Erkan & Evans, 2016
Theory of Motivation; Goal-Gradient Effect	Hull, 1932; Kivetz, Urminsky & Zheng, 2006	Kuppuswamy & Bayus, 2017; Zvilichovsky et al., 2018
Theory of Planned Behavior (TPB)	Ajzen, 1991	Cheung & Thadani, 2012; Shneor & Munim, 2019; Fu et al., 2015
Theory of Reasoned Action (TRA)	Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980	Cheung & Thadani, 2012; Chen et al., 2012; Gunawan & Huarng, 2015; Shneor & Munim, 2019

THEORETICAL LENSES	FUNDAMENTAL LITERATURE EXAMPLES	RELEVANT LITERATURE EXAMPLES
Unified Theory of Acceptance and Use of Technology (UTAUT)	Venkatesh, Morris, Davis & Davis (2003); Venkatesh, Thong & Xu, 2012	Chen et al., 2012; Kim & Hall, 2020
User Entrepreneurship Theory	Shah & Tripsas, 2007	Brem et al., 2017
User Innovation Theory	Von Hippel, 1986, 2005	Baldwin et al., 2006; Brem et al., 2017; Poetz & Schreier, 2012

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