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CONTENTS

TOWARDS A METAVERSE SHOPPING REVOLUTION: A MIXED-METHOD STUDY ON FACTORS INFLUENCING CONSUMERS' INTENTIONS TO ADOPT METAVERSE AS SHOPPING MARKETPLACE

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ABSTRACT

This study aims to understand the factors influencing consumers' intention to adopt the metaverse as a marketplace for physical products and the role of trust specifically focusing on the generation aged 18–28. It also explores the moderating role of trust towards the company Meta in these relationships. An exploratory sequential mixed-method research design was employed to develop an encompassing conceptual model, enhance hypothesis formulation, and validate findings through triangulation. In the first phase of the study, in-depth interviews were conducted with professionals and students ($n = 11$), and in the second phase, Likert-type questionnaire was administered ($n = 386$) to university students. The data collected in the second phase was analyzed using Covariance-Based Structural Equation Modeling (CB-SEM) to validate the conceptual model. This included Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) for reliability and validity, followed by the assessment of path coefficients. Double-mean centering was applied to test moderating effects, with all analyses conducted using the R software's lavaan package. The results confirmed the positive effects of novelty, relative advantage, realism, and compatibility on consumers' intention to adopt the metaverse as a marketplace for physical products, while complexity and financial costs were identified as barriers. Trust towards Meta did not have a moderating effect. The findings provide insights for managers to develop the metaverse in a customer-centric manner and promote its unique features while addressing complexity and financial concerns. The study extends the literature on the metaverse in the consumer goods sector and contributes to Innovation Adoption Theory.

KEY WORDS

metaverse, innovation adoption, metaverse retailing, diffusion of innovations

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1 INTRODUCTION

Stepping into the Metaverse opens doors where shopping transcends the boundaries of reality, transforming the act of purchasing physical products into a digital odyssey (Dwivedi et al., 2022). Envision a realm where every consumer desire awaits just a click away, liberated from the constraints of time and place. This vision consumes industry experts and enthralls minds worldwide (Koohang et al., 2023). However, the looming question remains: Are we truly prepared to embrace the virtual realm of commerce? (Mkedder and Das, 2024)

Recent findings underscore consumers' eagerness to engage with retailers (78%) and consumer goods companies (77%) within the Metaverse. Additionally, approximately 50% express their willingness to procure physical products within this digital domain (Preuss, 2022). These insights illuminate the burgeoning demand and opportunities for retailers and consumer goods companies to exploit the Metaverse as a marketplace for tangible products. However, within this potential lies hesitancy among people to fully embrace the Metaverse. A study conducted in the U.S. and the U.K. revealed that fewer than 20% of respondents believe brands should invest in branded experiences within this virtual space (Proulx, 2021; Mkedder and Das, 2024).

Furthermore, this trend aligns with the burgeoning body of research on the Metaverse, which witnessed a surge in relevant articles from 2019 onwards, peaking in 2021, coinciding with the company's rebranding (Trunfio and Rossi, 2022). To date, research has predominantly centered on computer science, engineering, and the Metaverse's potential for e-learning and medical education (Crespo-Pereira et al., 2023; Trunfio and Rossi, 2022). Nonetheless, there exists a profound need for additional exploration in various domains, including marketing and communication, particularly within the consumer goods and retail sectors where substantial investments have already been allocated (Huang et al., 2022). Numerous researchers, such as Tan et al. (2023), stress the imperative of comprehending consumer motivations concerning retailing and brand activities. Furthermore, Mkedder and Das (2024), and Dwivedi et al. (2022) specifically advocate for further research into technology adoption models and theories.

Previous research has extensively delved into people's inclinations to adopt the Metaverse, often employing various theoretical approaches (Toraman, 2022) such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). However, these studies have not specifically addressed the scenario of shopping for physical products within this digital realm. To bridge this gap, the current study employ the Diffusion of Innovation Model (DOIM) presents a novel approach yet to be explored in this context. Unlike the TAM, the DOIM encompasses five distinct attributes, providing a more intricate understanding of adoption processes (Al-Mamary et al., 2016). Demonstrating robustness, this model explains between 49–87% of the variance in adoption rates, offering pivotal insights for practitioners (Rogers, 1995).

Given the intricacies of technology adoption, qualitative methods have emerged as a promising avenue to unearth additional factors influencing adoption rates (Dehghani et al., 2022). Building upon this, the integration of mixed-method research designs has gained momentum, amalgamating robust quantitative measures from models like the DOIM with the nuanced, contextual insights garnered from qualitative research (Wunderlich et al., 2019). This approach facilitates a more comprehensive exploration of technology adoption, ultimately enriching our understanding of consumers' behavioral intentions (Creswell and Plano Clark, 2018).

In addition to delving into research regarding technology adoption theories, Dwivedi et al. (2023) and Mkedder and Das (2024) emphasize the necessity of delving deeper into the ethical challenges entwined with the Metaverse. A pivotal, unanswered query revolves around how consumers will evaluate and perceive matters of privacy and security within this domain. Addressing this concern, Tan et al. (2023)

shed light on the significance of relationship marketing, which heavily relies on the trust consumers place in service providers within the Metaverse. Notably, the company Meta stands as a pivotal force in the industry, rendering its role crucial and deserving of thorough comprehension.

Moreover, trust emerges as a significant concept shaping adoption decisions (Viardot, 2017). A lack of trust in an innovation, particularly in the online sphere, can inhibit adoption intentions (Mkedder et al., 2024b). This encompasses trust both in the innovation itself and in the entity or provider behind it. Focusing on the latter aspect, a Forrester study discovered that 75% of respondents harbor distrust toward Meta's involvement in developing the Metaverse (Proulx and Liu, 2021). Trust toward Meta is anticipated to moderate the relationship between innovation attributes and the intention to adopt the Metaverse as a marketplace for physical products. Consequently, users' trust levels toward Meta can mold their overall perceptions of the Metaverse, thereby influencing their readiness to embrace it. Understanding the role of trust toward Meta as a moderating factor is therefore imperative for researchers and managers seeking to bolster adoption of Metaverse retailing.

The current study adheres to the guidelines outlined by Venkatesh et al. (2013) for mixed-method research. The qualitative segment of the study aims to unearth additional factors pertinent to the adoption of the Metaverse as a marketplace for physical products. Subsequently, the quantitative phase tests the innovation attributes of the DOIM alongside factors identified in the qualitative phase, namely Realism, Novelty, and Financial Costs, along with the moderator Trust towards Meta. This study endeavors to address the following research questions: (1) What factors influence consumers' intention to embrace the Metaverse as a marketplace for physical products? (2) How does Trust towards Meta impact the relationships between adoption factors and consumers' intentions to adopt? Following insight that the metaverse is often perceived as an innovation designed primarily for younger audiences (Oxford Analytica, 2022), the current research focused on young participants aged 18–28.

Therefore, this research marks a pioneering addition to the existing knowledge base surrounding the Metaverse within the realm of retailing and consumer goods. By scrutinizing the moderating role of Trust towards Meta, this study ventures into uncharted territory, offering a fresh perspective on how the company influences the adoption of Metaverse retailing. The adoption of a mixed-method research design represents a novel approach with the potential to establish a new standard for investigating the adoption of innovative technologies. The findings of this study hold significant implications for both academia and industry, as they contribute to a deeper understanding of the Metaverse's evolution into a marketplace for physical products. Crucially, these insights empower managers with the tools to craft customer-centric experiences and make informed decisions regarding partnerships and promotional strategies.

2 THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Metaverse as a Marketplace for Physical Products

After Mark Zuckerberg (2021) announced the rebranding of Facebook to Meta in October 2021, the interest in the metaverse has experienced rapid growth (Google Trends, 2023). One of the emerging use cases is metaverse retailing, which can be considered the next iteration of e-retailing undertaken in a three-dimensional (3D) environment (Bourlakis et al., 2009). In this context, Illenberger (2022) distinguishes between digital and physical products. This research focuses on the latter, which encompasses real-time shopping experiences involving physical products. For this, the adoption of

spatial computing and specific hardware such as virtual, mixed, or augmented reality (AR) glasses are required to create an optimal user experience (Illenberger, 2022). According to industry experts' predictions, it will require approximately a decade to fully develop these foundational technologies and establish the metaverse as a marketplace for physical products (Nguyen et al., 2022; Toriello, 2021).

Despite its significance being limited to a future timeframe, researchers underline the importance of understanding the metaverse as a retail channel for physical products to foster customer-centric journeys (Dwivedi et al., 2022). In this context, Yoo et al. (2023) highlight that retailers must attain a deeper comprehension of how to design their product delivery in the metaverse considering consumers' perspectives. This implies that while the full realization of the metaverse as a marketplace for physical products may be several years away, it is imperative to commence our understanding of this emerging retail channel early on.

2.2 Innovation Adoption Theory

The Diffusion of Innovation Theory, originally proposed by Rogers (1995), presents a framework comprising five attributes that influence the adoption rate of innovations: Relative Advantage, Compatibility, Complexity, Trialability, and Observability. All the factors are interrelated but conceptually distinct from each other (van Rijnsoever et al., 2009). Furthermore, one fundamental aspect of the DOIM is that it regards these attributes as perceptions held by consumers rather than evaluations conducted by experts or companies within a specific field (Khosrow-Pour, 2007). This perspective emphasizes the subjective nature of innovation adoption, acknowledging that it is driven by individuals' perceptions and preferences.

The DOIM holds a prominent position in the scientific community and has been widely cited and researched, as highlighted by Hasan et al. (2019) in their comparative study of various innovation adoption theories. The model finds application across diverse disciplines, including marketing and consumer behavior studies, where it is considered especially valuable for analyzing consumers' adoption intentions of new technologies (Huang and Hsieh, 2012).

Despite its widespread acceptance, the DOIM has not been free of criticism in recent years. Meta-analyses have suggested that certain attributes may exert a stronger influence on adoption intentions than others (Kapoor et al., 2014). Furthermore, the significance of these factors can vary significantly in different contexts (Hasan et al., 2019; Tornatzky and Klein, 1982). This critique has prompted discussions about the need to extend the DOIM to better account for these variations, as proposed by Parthasarathy et al. (2021). It is evident that the framework may not universally apply to all innovation adoption scenarios. This represents a clear gap in our understanding of innovation adoption dynamics and underscores the evolving nature of this field of study. In the context of metaverse adoption, this might be even more pronounced as this emerging domain brings a new set of challenges and considerations. Understanding how the DOIM applies or requires adaptation within the metaverse realm is crucial for effectively navigating this evolving landscape.

Recognizing the limitations, mixed-method research approaches have gained popularity in the field of innovation adoption, as highlighted by Dehghani et al. (2022). By integrating both qualitative and quantitative methods, these approaches enable researchers to delve deeper into the complexities and dynamics of innovation adoption, offering a more holistic and nuanced understanding of this multifaceted phenomenon (Venkatesh et al., 2013).

One such mixed-method approach is exploratory sequential research, which can provide important insights that may not have been discovered through a singular method. This approach typically begins with a qualitative exploration study, where researchers delve into the subject matter in-depth, gathering rich qualitative data and insights. This qualitative phase helps identify key factors, and potential variables related to innovation adoption. These findings are then tested quantitatively with

a larger sample to validate and quantify the relationships discovered during the qualitative phase (Creswell and Plano Clark, 2018).

Exploratory sequential research offers several advantages in the context of studying innovation adoption. First, it allows for triangulation, which means that the qualitative and quantitative data can be compared and cross-validated, strengthening the overall reliability of the research findings. Second, this approach facilitates enhanced hypothesis formation. The qualitative phase often generates hypotheses or theories that can be rigorously tested during the quantitative phase, contributing to a more robust research framework. Lastly, it enables a comprehensive understanding of the researched topic. By combining qualitative insights with quantitative data, researchers gain a holistic view of the factors influencing innovation adoption, allowing for a deeper and more nuanced analysis (Wu, 2012). Thus, applying a mixed-method research design to study the metaverse as a marketplace for physical products can therefore be highly beneficial. The metaverse's innovative and multifaceted nature demands a thorough, multidimensional examination, which can be effectively addressed through both qualitative and quantitative methods. Building on the DOIM framework and findings from an exploratory study, we have identified factors that influence consumer intentions to adopt the Metaverse as a marketplace for physical products. These identified factors have subsequently guided the development of our hypotheses.

Relative Advantage refers to the perception that an innovation is superior to the existing solution regarding economic benefits, such as cost savings or increased social prestige (Rogers, 1995). Previous research in various fields confirms the positive influence of Relative Advantage on adoption intentions (Ismail, 2012; Kapoor et al., 2014). In the context of metaverse retailing, the advantages of the metaverse, such as increased convenience, three-dimensional product visualization, and uniqueness, make its use appealing to consumers (Hassouneh and Brengman, 2014). The positive influence of the attribute can also be explained by Expectancy Theory, which suggests that individuals are motivated to engage in a particular behavior when they believe their actions will result in desired outcomes or rewards (Majumdar, 2010). Looking at the interviews conducted, a substantial number of codes related to the factor Relative Advantage. Many interviewees saw opportunities and advantages in the metaverse compared to online shops or physical stores. The metaverse being a convenient and quick way to shop was mentioned by 73% of respondents. Consequently, the first hypothesis was proposed as follows:

H_1: *Relative Advantage has a significant positive effect on the intention to adopt the metaverse as a marketplace for physical products.*

Compatibility refers to the consistency of an innovation with consumers' existing values, experiences, and needs (Rogers, 1995). Studies applying the DOIM have consistently found a positive relationship between Compatibility and adoption intentions (Ismail, 2012; Kapoor et al., 2014). In augmented reality (AR) shopping applications, Compatibility with consumers' existing shopping practices positively influences adoption intentions (Jiang et al., 2021). Given that the metaverse incorporates AR technologies, it is expected that Compatibility will similarly affect the intention to adopt it. This notion was confirmed during the interviews. The ability of the metaverse to extend the physical world and seamlessly integrate with existing user devices seems to enhance consumers' perception and their intention to adopt the metaverse as a marketplace for physical products. Therefore, the following hypothesis 2 was proposed:

H_2: *Compatibility has a significant positive effect on the intention to adopt the metaverse as a marketplace for physical products.*

Complexity refers to the perceived difficulty of understanding and using an innovation (Rogers, 1995). Innovations perceived as more complex require additional learning and may hinder adoption (Hoeffler, 2003). While the influence of Complexity on adoption intentions has been mixed in previous studies, the

factor seems to be significant in the metaverse context. A survey revealed that a low percentage of consumers understand what the metaverse is (Anderson, 2022). Additionally, the use of metaverse technologies like virtual reality headsets can pose physical discomfort (Hamad and Jia, 2022). The issue can be further explained by Cognitive Load Theory, which suggests that individuals' cognitive resources become overloaded when faced with complex tasks or systems, leading to reduced motivation and performance (Plass et al., 2010). The Complexity of the metaverse as a marketplace for physical products can overwhelm users, resulting in decreased intention to adopt due to the perceived cognitive burden. This is in line with interviewees' expectations and apprehensions. Many respondents stated that metaverse (technologies) should be easy to use, intuitive, and not too overwhelming for the user. Thus, hypothesis 3 was proposed in the following way:

H_3: *Complexity has a significant negative effect on the intention to adopt the metaverse as a marketplace for physical products.*

Trialability refers to the extent to which consumers can experiment with an innovation (Rogers, 1995). Studies have shown mixed results regarding the impact of Trialability on adoption intentions, with varying effects based on the context and associated costs (Ismail, 2012; Jiang et al., 2021). In the case of the metaverse, high initial costs associated with hardware and unfamiliarity may lead consumers to hesitate. Offering opportunities for consumers to trial the metaverse as a marketplace for physical products could increase adoption intentions, as it allows them to experience the benefits firsthand. This expectation is in line with Experiential Learning Theory, which posits that individuals acquire knowledge and attitudes through experimentation and reflective observation, including direct product experience (Lantos, 2015). Even though only 2 out of 4 sub-categories related to Trialability were identified in the interviews, an adequate number of respondents expressed their desire to try the metaverse before full adoption, especially due to the high costs for equipment. Hypothesis 4 was proposed as follows:

H_4: *Trialability has a significant positive effect on the intention to adopt the metaverse as a marketplace for physical products.*

Examining the importance of Financial Costs in innovation adoption, several studies are consistent with the findings of the interviews and confirm a significant negative effect of perceived costs on adoption decisions (Hanafizadeh et al., 2014; Kim et al., 2013; Twum et al., 2022). This effect can be explained by Loss Aversion Theory, which states that individuals tend to focus more on potential losses than gains when making decisions that involve behavioral change (Kahneman and Tversky, 1979). Since metaverse retailing is considered a successor to conventional e-retailing (Bourlakis et al., 2009), it is expected that similar results will occur. This is in line with the majority of interviews. Respondents mentioned that additional devices and payments present a barrier to metaverse retailing adoption. Consistent with the qualitative interviews conducted in phase one, a larger global study in 2019 revealed that the price of VR headsets is the leading barrier to mass adoption of VR (Ahmed, 2022; VR Intelligence, 2019). Based on the insights from the qualitative interviews and past research, hypothesis 5 was added as follows:

H_5: *Financial Costs has a significant negative effect on the intention to adopt the metaverse as a marketplace for physical products.*

The importance of Perceived Realism was emphasized during the interviews extensively. The construct emerged recently in Innovation Adoption Theory with the evolution of technologies such as AR (Daassi and Debbabi, 2021). Realism in the context of the metaverse can be defined as the extent to which users perceive the virtual environment and its content as realistic and immersive (Gilbert, 2016). Therefore, a high level of Realism results in products and user activities being viewed as natural and authentic (Daassi and Debbabi, 2021). Kalantari and Neo (2020) highlight that the lack of Perceived Realism and immersion is a fundamental challenge in designing fully

immersive virtual environments. Specifically for VR technologies, Vishwakarma et al. (2020) confirmed that perceived immersion leads to higher perceived value among consumers, leading to higher intentions to adopt virtual reality. A study conducted in the area of AR-based apps supports this notion. Daassi and Debbabi (2021) found that Perceived Realism offers consumers more compelling experiences, leading to higher attractiveness and intention to reuse AR apps. During the interviews in phase one, respondents also emphasized the importance of products being as close to reality as possible. Moreover, interviewees highlighted the need for the metaverse marketplace to imitate real-life experiences. Based on these insights, hypothesis 6 was proposed as follows:

H_6: *Realism has a significant positive effect on the intention to adopt the metaverse as a marketplace for physical products.*

Novelty is the third attribute that emerged during the interviews and refers to the extent to which consumers perceive an innovation to be a new and exciting alternative to an existing technology (Wells et al., 2010). Perceived Novelty significantly impacts product evaluation, customer satisfaction, and intention to adopt (Talukdar and Yu, 2021), which in turn can positively influence consumers' purchase intentions. Wells et al. (2010) investigated the role of perceived novelty in information technology (IT) innovation adoption and found a significant effect on perceived risk, perceived reward, and attitude toward usage. Positive attitudes towards an innovation can thereby be seen as a key driver of consumers' intention to adopt it (Mazambani and Mutambara, 2020). The desire to experience something new and have access to special products that are purchasable exclusively in the metaverse was also expressed by interviewees. In line with the qualitative interviews, 57% of U.S. consumers look forward to experiencing things in the metaverse that they would typically not experience (Sitecore Corporation, 2022). Based on the consistent findings from the qualitative interviews and the literature review, the following hypothesis 7 was proposed:

H_7: *Novelty has a significant positive effect on the intention to adopt the metaverse as a marketplace for physical products.*

2.3 The Moderation Role of Trust on Meta

Trust is vital for cultivating positive relationships between individuals and organizations, providing the basis for cooperation and the sharing of information (Oleszkiewicz et al., 2024). Online environments, which are closely related to the metaverse concept, have long been recognized as requiring a high degree of trust for successful adoption and usage. Wongkitrungruen et al. (2020) underline the critical nature of trust for users in digital environments where face-to-face interaction is absent. The perception of trustworthiness in online platforms influences consumers' decisions to transact and purchase products in a virtual environment.

Sudirjo et al. (2024), in a recent study on online shopping, found that there is a strong link between trust and a company's reputation. The reputation of a business or organization has been shown to directly influence consumers' trust in their products or services. Customers are more likely to trust and engage with entities with positive reputations, making reputation management a critical aspect of building trust in online settings. Furthermore, in virtual environments, data privacy and cyber security have been demonstrated to be significant indicators of consumer trust (Dhami et al., 2013). The metaverse, being a digital realm that often involves the exchange of personal information and digital assets, raises concerns about data security and the protection of users' privacy. These concerns can erode trust in an innovation and impede its widespread adoption.

Given these insights, it's crucial to consider the role of Meta (formerly Facebook) in shaping the metaverse. Meta is a key player in this emerging digital realm, wielding significant influence over its direction and evolution. Previous research about Facebook and consumer surveys about Meta demonstrate a lack of trust related due to low cyber security and

data privacy (Proulx and Liu, 2021). On the one hand, previous research demonstrates that lower levels of perceived security, privacy, and trust lead to decreased information sharing intentions (Dhami et al., 2013). On the other hand Nguyen et al. (2024) argued that benefits of social networks outweigh the risks of disclosing information. Due to these divergent results, further insights are needed to gain clarity on the dynamics of trust in the metaverse context.

Despite the growing relevance of trust in the metaverse and Meta's pivotal role, there remains a noticeable gap in the existing literature. Only a few studies have systematically investigated the role of trust in shaping user behaviors, attitudes, and intentions within this emerging digital landscape. Especially when it comes to Meta, more insights are required to better understand the company's role in this context. Consequently, there is an evident and pressing need for research that delves into trust and its implications for metaverse adoption and user behavior. Closing this knowledge gap is essential for comprehending the dynamics of trust in the metaverse and for better understanding the influence of key players like Meta in shaping the future of this digital realm.

Trust plays a crucial role in innovation adoption and is expected to be a significant factor in the metaverse context. Extensive research in various domains has demonstrated the impact of trust on adoption intentions (Pham et al., 2024; Aldboush and Ferdous, 2023). Significant moderating effects were found by Chen et al. (2015), Hamakhan (2020), and Alsaad et al. (2017), indicating that consumers perceive innovation attributes more favorably if they have a high level of trust in the innovation, ultimately influencing their willingness to adopt. Muharam et al. (2021), discovered that consumers who have a high level of trust in a company are more likely to positively evaluate the quality of a service, leading to increased satisfaction with the overall service experience.

In the context of the metaverse, concerns about safety and security act as barriers to adoption (Hassouneh and Brengman, 2014). This was also mentioned by a small number of respondents during the interviews. The association between the company Meta (formerly Facebook) and data privacy issues may thereby contribute to low consumer trust. Drawing from Relationship Marketing Theory, trust serves as a foundational element in building and maintaining strong customer relationships (Thaichon and Ratten, 2020). Trust towards Meta can be seen as a form of trust in the provider-customer relationship, where Meta is viewed as a reliable and trustworthy partner (Kleinaltenkamp and Ehret, 2006). Since a substantial share of consumers mistakenly believe that the metaverse is exclusively owned by the company Meta (Wright, 2022), it is likely that (lack of) trust in the company will transfer to the metaverse industry and innovation as a whole. Based on the theoretical findings and interviews, the following hypothesis 8 was proposed:

H_{8a-g}: *Trust towards Meta moderates the relationships between each of the following innovation attributes (a) Relative Advantage, (b) Compatibility, (c) Complexity, (d) Trialability, (e) Financial Costs, (f) Realism, and (g) Novelty, and their respective impacts on the intention to adopt the metaverse as a marketplace for physical products.*

3 METHODOLOGY AND DATA

3.1 Exploratory Study (Study I)

The research at hand employed a mixed-method approach, i.e., an exploratory sequential design involving two phases of data analysis. The primary goal of the qualitative study was to explore factors affecting consumers' intention toward adopting the metaverse as a marklace for physical products in addition to the predefined factors of the DOIM. These factors together were used to develop a theoretical framework explaining their relationship, which was tested in phase two.

Tab. 1: Profile of interview respondents ($n = 11$)

Respondent	Sex	Age	Position	Residency	VR/Metaverse Experience
111	Female	23	Marketing Management Student	The Netherlands	No experience
204	Female	28	Brand Manager	Switzerland	Limited experience with VR headsets at congresses
867	Male	27	Global IT Support	Germany	Moderate experience with HoloLens at work
645	Male	31	Sales	Germany	No experience
762	Male	25	Recruitment Marketeer	The Netherlands	Extensive experience with VR at home and limited experience with HoloLens at work
197	Female	22	Innovation Management Student	The Netherlands	Limited experience with VR at an exhibition
287	Male	28	Innovation Manager	Spain	Extensive experience with the metaverse at work and at home
489	Female	42	Brand Director	Switzerland	Limited experience with VR at congresses
328	Male	51	Global XR Technology and Metaverse Lead	The Netherlands	Extensive experience with the metaverse at work and at home
716	Male	24	Marketing Manager	Germany	No experience
593	Female	32	Customer Experience Manager	The Netherlands	Moderate experience with VR at home and at work

In-depth interviews were conducted with a small sample of 11 respondents. Interviews are a powerful method to explore individuals' thoughts and behaviors (Boyce and Neale, 2006). In the context of this study, the interviews provided valuable insights into the factors that are important in consumers' decision-making process regarding adopting the metaverse as a marketplace for physical products. Respondents were selected using purposive maximum variation sampling. This method allows for obtaining a broad view of the research topic from different perspectives (Etikan et al., 2016; Mkedder et al., 2024a) and is recommended for the qualitative phase in mixed-method research approaches (Wachter Morris and Wester, 2018). Since the population of online shopping users is very broad and diverse, with several 2.14 billion in 2022 (Rajnerowicz, 2023), it was essential to include consumers with different key demographics such as age and gender, as well as varying levels of experience with metaverse technologies. Also, professionals enrich the dataset with a range of practical experiences and specialized knowledge (Etikan et al., 2016).

The sample consisted of 2 students and 9 professionals working in different fields. The respondents' ages ranged from 22 to 51 years old; 6 of the respondents were males (55%), and 5 were females (45%). Their experience with the metaverse varied from no experience to extensive experience with metaverse technologies, such as VR, in work and home settings. An overview of participants' profiles is displayed in Tab. 1.

Semi-structured interviews were conducted with the interviewees, allowing for consistency and flexibility simultaneously (Leavy, 2014). All interviews were conducted one-on-one and lasted 15–20 minutes. The interviewees were asked for their consent before the interviews commenced. An explanation of the metaverse as a marketplace for physical products was given to ensure a common understanding of the topic. This was followed by the main open-ended question: "Which factors are important to you to decide whether to shop for physical products in the metaverse?" Following the process of semi-structured interviews, follow-up questions and probes were used to gain a deeper understanding of the main drivers

and barriers mentioned by the interviewees (Salmons, 2015). All interviews were recorded and transcribed. Anonymity and confidentiality were guaranteed by data pseudonymization of interview protocols, assigning three-digit codes to interviewees (Flick, 2021).

To analyze the interviews, thematic analysis following a grounded theory methodology with a combined approach of deductive and inductive coding was employed. Recent research suggests that a combination of deductive and inductive methods is particularly suitable for mixed research methods, such as exploratory sequential designs (Proudfoot, 2023).

In the first step, the researcher deductively analyzed the interview transcripts, looking for codes related to the five innovation attributes from the DOIM. This was approached by scanning for keywords related to the constructs and items used in respective measurement scales (Moore and Benbasat, 1991). In the second step, inductive coding was employed to generate open codes that addressed constructs not captured by the DOIM. For this, in-vivo coding, i.e., extracting meaningful words directly from the data, as well as descriptive coding, i.e., summarizing the topic in a word or short phrase, was applied (Saldaña, 2012). The third step involved axial coding to identify underlying sub-categories based on the newly emerged open codes. In the last step, higher-order categories were developed through selective coding and a review of literature in the field of innovation adoption. For each theme, the axial and open codes extracted from the data were compared with existing constructs used in Innovation Adoption Theory. This process led to the addition of new constructs, serving as additional independent variables in the final theory to be tested in phase two of the study.

3.2 Confirmatory Study (Study II)

The current study utilizes Structural equation modeling (SEM) to analyze and validate the conceptual model. Two SEM offers two primary approaches for analyzing relationships within a model. Partial Least Squares SEM (PLS-SEM) is exploratory, focusing on theory prediction and development, whereas covariance-based SEM (CB-SEM) is employed to confirm or refute theories and their associated hypotheses (Hair et al., 2021). Given that the model in this research draws from the DOIM and integrates insights from the qualitative study, the objective of the SEM analysis was to assess the conceptual model and its hypotheses. Consequently, CB-SEM was deployed in two stages, encompassing the analysis of the measurement model and the structural model.

To ensure the reliability of the measurement relationships between items and latent variables in the model, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted first (Harrington, 2009). In the second step, the relationships between latent variables were tested by analyzing path coefficients and their statistical significance. This two-step approach allowed to enhance the validity and reliability of the analysis. All analyses were performed using R. Specifically, the R package lavaan was utilized for the CFA and SEM. To test moderating effects, double-mean centering was used to specify the interaction terms, mitigating potential issues of multicollinearity (Wiberg et al., 2018).

A questionnaire was chosen as the data collection method for the confirmatory study. To ensure academic integrity, informed consent was obtained from all participants at the beginning of the questionnaire (Rose et al., 2014). Participants were required to read and agree to the conditions of the study before answering any content-related questions. Moreover, respondents were informed about the right to withdraw from the study at any time (Weathington et al., 2012). To maintain anonymity and confidentiality, no (combination of) personal information that could identify respondents was requested in the questionnaire (Esteban-Bravo and Vidal-Sanz, 2021). Further, to minimize bias among the respondents about what we mean by the Metaverse as a marketplace for physical products, a definition of the metaverse and examples of physical products were included in the questionnaire's introduction.

Tab. 2: Profile of questionnaire respondents ($n = 386$)

Variable	Group	Frequency	Percentage
Age	18–23	338	87.56
	24–28	44	11.40
	33–38	4	1.04
Gender	Male	264	68.39
	Female	119	30.83
	Other	1	0.26
	Prefer not to say	2	0.52
VR/AR Experience	None at all	35	9.07
	Limited	216	55.96
	Moderate	119	30.83
	Extensive	16	4.14
Privacy concerns	Not at all	25	6.48
	Slightly	158	40.93
	Moderately	129	33.42
	Very much	74	19.17
Social influence	Not at all	25	6.48
	Somewhat	124	32.12
	Moderately	151	39.12
	Very much	86	22.28

Each construct in the model was measured using an appropriate and widely used measurement scale. The scales were adjusted to fit the context of metaverse retailing, resulting in 39 items, as shown in the Appendix. All items were measured on 7-point Likert scales, offering sufficient response options for nuanced measurement while maintaining simplicity for respondents (Russell and Purcell, 2009). Demographic questions about age and gender were included at the end of the questionnaire. Furthermore, respondents were asked about their prior experience with VR/AR, their privacy concerns, and the expected use of the metaverse within their social network. These factors were presumed to influence respondents' perceptions and were therefore used as control variables in the data analysis to better isolate and understand the direct effect of perceived innovation attributes.

To collect the data, a sample of 396 university students from the VU Amsterdam School of Business and Economics was recruited. University students were chosen for this study due to their typically heightened engagement with digital platforms and virtual environments, both critical aspects of the metaverse (Prensky, 2001; Oblinger and Oblinger, 2005; Mkedder and Özata, 2024). Additionally, students generally possess greater familiarity with and reliance on digital technologies compared to the wider population (Mkedder et al., 2024a). This demographic is frequently leveraged in technology adoption research, highlighting their relevance (Kim et al., 2013; Schepers and Wetzels, 2007). Given their proclivity to be early adopters, this segment constitute an ideal cohort for examining behaviors and attitudes towards emerging technologies like the metaverse (Molina-Castillo et al., 2023). Data collection took place between the 14th and 15th of March 2023 using Qualtrics, leading to 386 valid responses. The mean age of participants was 21.6 years, with a standard deviation of 2.1. Among the participants, 68% identified as male and 31% as female. Most participants had limited VR/AR experience (56%), slight to moderate privacy concerns (74%), and expected their social network would use the metaverse somewhat to moderately in the future (71%). A summary of the demographic characteristics of the respondents is provided in Tab. 2.

4 RESULTS

4.1 Study I Results

Based on the interviews, three other innovation attributes in addition to the five innovation attributes of the DOIM were identified: Financial Costs, Realism, and Novelty. Furthermore, many respondents mentioned during the interviews that their decision to use the metaverse as a marketplace for physical products depends on the product type. However, since research in the metaverse retailing field emerged recently (Yoo et al., 2023), there are no specific insights yet on which products will be more or less favorable to purchase in the metaverse. Therefore, the research decided not to consider the factor and continued focusing on the general category of "physical products". Tab. 3 provides an overview of the thematic analysis that was conducted.

Examining the five innovation attributes of the DOIM, participants mentioned themes related to 4 out of 5 constructs. None of the respondents mentioned Observability as a factor influencing their decision to enter the metaverse. This observation is in line with previous meta-analyses that found no significant effect of Observability on adoption intentions (Kapoor et al., 2014). Furthermore, the construct-wise alpha score for Observability was found to be 0.676, which did not meet the acceptable threshold of 0.7 (Hair et al., 2010). Dropping items from the scale did not lead to an improvement in the score. For these reasons, the decision was taken to delete the construct observability from the conceptual model.

The results from the first phase of the study led to the inclusion of the constructs Financial Costs, Realism, and Novelty to complement the existing five constructs of the DOIM, i.e., Relative Advantage, Compatibility, Complexity, Observability, and Trialability. As suggested by Pandit (1996), a literature comparison was conducted for each of the constructs as well as the moderator before the hypotheses and the conceptual model were derived. The results from study I, combined with the literature review, provide a solid foundation for the final conceptual model as illustrated in Fig. 1. This model was then tested using quantitative research methods in study II.

4.2 Study II Results

4.2.1 Measurement Model

The content validity and reliability of the measurement scales were assessed first. Reliability was examined by observing Cronbach's alpha coefficient, with a threshold value of 0.7 (Hair et al., 2010). All Cronbach's alpha scores, excluding the construct Observability which was removed from the conceptual model as explained in the methodology section, indicated satisfactory levels of reliability, as the results in Tab. 4 show.

In the next step, the EFA was conducted to examine whether the underlying items accurately measure the intended constructs (Cooper, 2018). Following the recommendation of Hwang and Lee (2022), separate EFAs were performed for dependent, moderating, and independent variables. A non-parametric method, i.e., MLR, was employed as the Mardia's skewness and kurtosis test revealed significant deviation from multivariate normality with a skewness test statistic of 18,280.83 ($p < 0.05$) and a kurtosis test statistic of 35.61 ($p < 0.05$), see Thode (2002). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were utilized to assess how suitable the data are for factor analysis. A KMO value greater than 0.5 indicates good sampling adequacy, while a significant Bartlett's test result implies sufficient intercorrelation among the variables to proceed with factor analysis (Child, 2006).

With a KMO value of 0.92 and a significant Bartlett's test result ($\chi^2 = 5{,}708.05$, $p < 0.05$), it was determined that the data for exogenous variables were suitable for EFA. The results of the EFA revealed the identification of seven factors through parallel analysis. As a rotation method, oblique rotation, specifically oblimin, was specified to allow for correlations between the innovation attributes (van Rijnsoever et

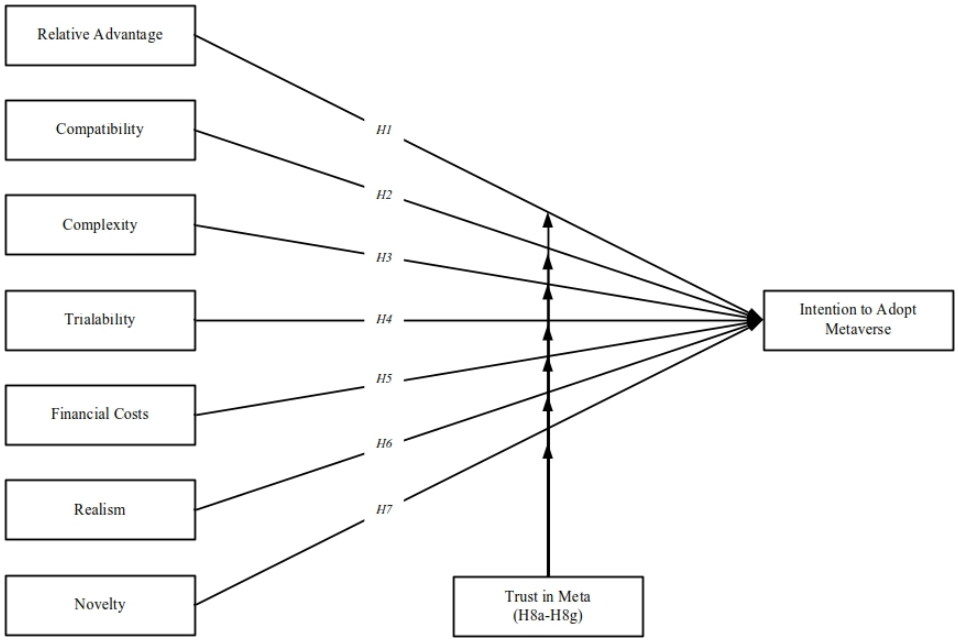

Fig. 1: Framework of the Study

al., 2009). Three items, CA4, TR1, and RE3, were removed from further analyses as their factor loadings were below the commonly applied threshold of 0.5 (Hair et al., 2010). The requirements for the EFA for the endogenous variable were also met. The KMO value was identified at 0.76, and Bartlett's test yielded significant results ($\chi^2 = 959.54$, $p < 0.05$). A single factor was identified with all factor loadings exceeding the threshold of 0.5. Finally, the EFA was performed for the moderating variable. The KMO value was satisfactory at 0.81, and Bartlett's sphericity test produced significant results ($\chi^2 = 1{,}452.46$, $p < 0.05$). Unexpectedly, two factors were identified instead of one single. TM1–4 and TM5–6 loaded on separate factors. Consequently, TM5 and TM6 were not included in the subsequent CFA and SEM analysis.

Model fit, convergent validity, and discriminant validity were assessed as part of the CFA. Commonly used fit indices, including SRMR, GFI, TLI, IFI, CFI, and RMSEA, were considered to evaluate the model fit (Hwang and Lee, 2022; Pituch and Stevens, 2015). As shown in Tab. 5, all fit indices indicated a satisfactory model fit for the measurement model.

Convergent validity was examined by assessing the construct reliability (CR) and average variance extracted (AVE) indices for each measured variable. A CR value of 0.7 or higher and an AVE value of 0.5 or higher are typically considered indicative of convergent validity (Hair et al., 1987; Nunnally, 1978). As presented in Tab. 4, the CR values ranged from 0.768 to 0.932, and the AVE values ranged from 0.522 to 0.820, demonstrating that all constructs met the respective criteria for convergent validity. Furthermore, discriminant validity was assessed, referring to the distinctiveness of measurements, indicating that they have low correlations with each other and can be treated as separate constructs (Campbell and Fiske, 1959). It was verified by comparing the AVE square root with the correlation coefficients between the construct and other constructs (Fornell and Larcker, 1981). The results are presented in Tab. 6. All AVE square roots are larger than the correlation coefficients with other constructs, ensuring discriminant validity.

4.2.2 Structural Model

SEM path analysis was applied in two steps to examine the relationships in the research model.

Tab. 3: Overview of thematic analysis

Construct	Sub-category	Significant Statement Examples	*f*	%
		Diffusion of Innovation Model		
Relative Advantage	Quickly	"Timewise it would be a benefit." (762)	8	72.73
	Easy	"The goal is to just stay at home and have an easy purchase." (197)	6	54.55
	Convenient	"The purpose is to not have the inconvenience of going to a shop or log in on a web page." (197)	8	72.73
	Advantageous	"I think it's very important that there's a clear advantage of the metaverse." (716)	9	81.82
Compatibility	Lifestyle	"… see if it fits what I need." (593)	1	9.09
	Current way to shop	"That same experience you want to have in an in a shopping world which is virtual." (328)	1	9.09
	Shopping style	"… if it delivers good products like the same products I could get in the store." (762)	4	36.36
	Current situation	"… connected to existing solutions like a store or an online shop, where you could seamlessly move from one to the other" (489)	4	36.36
Complexity	Cumbersome	"… have the hassle …" (489)	6	54.55
	Frustrating	"… not too overwhelming." (204)	1	9.09
	Difficult to use	"The most important for me is it's easy to use." (645)	7	63.64
	Mental efforts	"You need to get used to it, to get familiar with it." (197)	3	27.27
Trialability	Desire to try	"I really think I would try it." (716)	2	18.18
	Expectation to try	Not mentioned	0	/
	Use on a trial basis	Not mentioned	0	/
	Trial before decision	"I would test it and if it's easy to use and there are no problems, or I see the advantage compared to the real world, I definitely would use it." (645)	4	36.36
Observability	How to use	Not mentioned	0	/
	See if beneficial	Not mentioned	0	/
	Get clarity	Not mentioned	0	/
	Become apparent	Not mentioned	0	/
		Additional constructs		
Financial Costs	Additional devices	"I would be more likely to buy things in the metaverse if I don't need any additional gadget." (111)	9	81.82
	Payments	"The platform should not have many costs for the customer." (645)	8	72.73
Realism	Products close to reality	"Consistency with what I see in reality." (204)	9	81.82
	Realistic platform design	"The frames would need to be high, the frames per second in any virtual reality headsets." (762)	4	36.36
Novelty	New experience	"I need to experience something new." (287)	5	45.45
	Special products	"If they would do special products that you can only buy in the metaverse and not in an online store or in physical stores, that would also be a factor where I would consider going in the metaverse." (716)	2	18.18
Product type	Product type	"… depends on what product you buy." (197)	5	45.45

Note: excluding newly emerged categories that were mentioned in less than 4 interviews.

In the first step, the direct causal relationships between the seven innovation attributes and consumers' intention to adopt the metaverse as a marketplace for physical products were observed. In the second step, separate models were used to test the moderating role of Trust towards Meta.

Next to the seven innovation attributes and the dependent variable, the structural model included the control variables age, gender, VR/AR experience, social influence, and privacy concerns. The fit indices for the structural model were again satisfactory and met all the requirements. The path estimates of the constructs are shown in Tab. 7, providing evidence for hypotheses H_{1-3} and H_{5-7}. However, Trialability was found to be statistically insignificant ($\beta = 0.075$, $p = 0.342$), leading to the rejection of H_4.

Notably, Novelty exhibited the highest impact on metaverse retailing adoption intentions, with the highest estimate and lowest signifi-

Tab. 4: Reliability and convergent validity analysis

Construct	Loadings	Cronbach's alpha	CR	AVE
RA (Relative Advantage)	[0.653; 0.885]	0.902	0.903	0.701
CA (Compatibility)	[0.453; 0.879]	0.924	0.925	0.804
CX (Complexity)	[0.650; 0.826]	0.806	0.810	0.522
TR (Trialability)	[0.315; 0.813]	0.765	0.768	0.528
RE (Realism)	[0.414; 0.775]	0.820	0.829	0.618
FC (Financial Costs)	[0.668; 0.878]	0.816	0.819	0.603
NO (Novelty)	[0.636; 0.805]	0.802	0.811	0.596
IA (Intention to Adopt the Metaverse)	[0.866; 0.930]	0.932	0.932	0.820
TM (Trust Towards the Company Meta)	[0.834; 0.901]	0.849	0.925	0.757

Tab. 5: Fit indices for confirmatory factor analysis

Index	SRMR	GFI	TLI	IFI	CFI	RMSEA
Baseline	< 0.08	> 0.8	> 0.9	> 0.9	> 0.9	< 0.08
Observation	0.040	0.912	0.970	0.974	0.974	0.037

cance ($\beta = 0.483$, $p < 0.001$). As expected, Complexity ($\beta = -0.128$, $p = 0.040$) and Financial Costs ($\beta = -0.132$, $p = 0.011$) demonstrated a negative effect on the intention to adopt the metaverse as a marketplace for physical products, while the other innovation attributes played a favorable role.

Regarding the control variables, social influence ($\beta = 0.210$, $p < 0.001$) and VR/AR experience ($\beta = 0.135$, $p = 0.050$) had significant effects. To further understand the impact of these control variables, a comparison was made between the model that included the covariates and a model that excluded them. Notably, the inclusion of the control variables led to an increase in the significance of the innovation attributes. This implies that controlling for social influence and VR/AR experience allowed for a more accurate assessment of the relationship between the innovation attributes and the adoption of the metaverse as a marketplace for physical products. The path coefficients between age ($\beta = -0.006$, $p = 0.998$), gender ($\beta = 0.143$, $p = 0.141$), privacy concerns, and the dependent variable were statistically insignificant. This implies that, within the framework of this research model and when considering other influential variables, these factors have no notable impact on consumers' adoption decisions.

Tab. 6: Discriminant validity analysis ($n = 386$)

	RA	CA	CX	TR	RE	FC	NO	IA	TM
RA	0.837								
CA	0.667	0.897							
CX	−0.388	−0.359	0.722						
TR	0.389	0.375	−0.214	0.726					
RE	0.447	0.599	−0.203	0.281	0.786				
FC	0.066	0.019	0.058	−0.012	0.114	0.777			
NO	0.389	0.457	−0.172	0.372	0.426	0.178	0.772		
IA	0.601	0.666	−0.379	0.451	0.546	−0.009	0.519	0.906	
TM	0.283	0.312	−0.005	0.214	0.425	0.019	0.252	0.329	0.870

Note: AVE square roots are highlighted in hold.

Tab. 7: Model estimation without moderators ($n = 386$)

Hypothesis	Path	Standardized estimate	Standard error	z-value	p-value	Result
H_1	RA → IA	0.245	0.079	3.104	0.002	Confirmed
H_2	CA → IA	0.250	0.084	2.986	0.003	Confirmed
H_3	CX → IA	−0.128	0.062	−2.057	0.040	Confirmed
H_4	TR → IA	0.075	0.079	0.949	0.342	Rejected
H_5	FC → IA	−0.132	0.052	−2.556	0.011	Confirmed
H_6	RE → IA	0.209	0.070	2.998	0.003	Confirmed
H_7	NO → IA	0.483	0.122	3.967	< 0.001	Confirmed

Tab. 8: Moderation effects

H	IV	DV	Standardized estimate	Standard error	z-value	p-value	Result
H_{8a}	RA	IA	0.034	0.080	0.432	0.666	Rejected
H_{8b}	CA	IA	−0.025	0.079	−0.313	0.754	Rejected
H_{8c}	CX	IA	−0.001	0.040	−0.026	0.979	Rejected
H_{8d}	TR	IA	−0.054	0.051	−1.067	0.286	Rejected
H_{8e}	RE	IA	0.049	0.059	0.836	0.403	Rejected
H_{8f}	FC	IA	−0.047	0.043	−1.098	0.272	Rejected
H_{8g}	NO	IA	0.041	0.093	0.443	0.658	Rejected

The moderation effect was assessed through an additional structural model that incorporated the interaction terms between the innovation attributes and the moderating variable. The moderating role of Trust towards Meta could not be confirmed. Therefore, hypothesis 8 was rejected due to insignificant results. The estimates for each construct and moderator are presented in Tab. 8.

5 DISCUSSION AND CONCLUSIONS

The current study endeavors to delve into the factors influencing consumers' inclination to embrace the metaverse as a marketplace for physical goods, while also exploring the impact of trust in Meta. Analysis revealed that consumers' perception of the metaverse as novel, advantageous, realistic, and compatible positively influences their intention to adopt it for shopping physical products. Conversely, viewing the metaverse as complex and expensive diminishes consumers' adoption intentions.

Three hypotheses (H_1, H_2, H_3) rooted in the DOIM were confirmed, while one (H_4) was rejected. Additionally, all three hypotheses (H_5, H_6, H_7) derived from qualitative in-depth interviews garnered support. These findings furnish valuable insights for crafting the metaverse as a customer-centric marketplace for physical products, thereby bolstering its adoption rate.

Setianti et al. (2024) underscore that relative advantage significantly enhances trust levels, website perceptions, and attitudes toward online commerce. This aligns with Kapoor et al.'s (2014) meta-analysis, accentuating the importance of presenting the metaverse as an advancement to traditional e-retailing. It's imperative to spotlight metaverse features that add value to customers, such as online social interaction, personalization, and enhanced product visualization (Hennig-Thurau et al., 2022).

Compatibility emerges as a significant predictor of innovation adoption (Jiang et al., 2021; Kapoor et al., 2014). This study reaffirms its relevance in metaverse retailing adoption, ad-

vocating for a seamless transition from existing solutions to the metaverse, considering consumers' online shopping habits and preferences. Integrate frequent devices to facilitate a smooth transition when building the metaverse as a marketplace for physical products. Moreover, ensure seamless connections to existing websites and platforms, enabling consumers to navigate effortlessly between conventional online shops and the metaverse.

Novelty emerged as a highly influential factor in metaverse retailing adoption. Novelty emerged as a highly influential factor in metaverse retailing adoption. This finding is consistent with Mkedder et al. (2024b) and Talukdar and Yu's (2021) research on virtual reality, which highlights the importance of presenting the metaverse as a unique technology that enriches the shopping experience. As such, it is advisable to emphasize innovative features such as virtual showrooms and interactive product displays when marketing the metaverse as a marketplace for physical products. Additionally, innovative strategies, such as integrating real users and products into the metaverse and refining pricing strategies, can promote social interactions among different market participants including platforms, producers, consumers, and their avatars, as suggested by Zhang and Ye (2023).

On the other hands, realism plays an essential role in metaverse retailing adoption particularly regarding shopping for physical products. This finding confirms the findings of Daassi and Debbabi (2021) and extends them from an AR to the metaverse context more broadly. Consequently, companies should invest in Digital Twinning and accelerate the progress of underlying technologies, such as the Internet of Things and Machine Learning (Fuller et al., 2020). This ensures that the metaverse marketplace and the products offered within it will be represented as realistically as possible, leading to higher customer satisfaction, positive word-of-mouth, and higher intentions to (re)purchase.

Contrary to Jiang et al.'s (2021) findings, this study confirms the significant influence of Complexity as a barrier in the metaverse context. Similarly, Farajnezhad et al. (2021) also emphasize the significant link between DOIM and complexity. Therefore, it is crucial to simplify the user experience by designing an intuitive and effortless interface for consumers. Explicit guidance and visual aids facilitate consumers' navigation and interaction within the metaverse marketplace, thus minimizing cognitive load and expediting users' acclimation to the novel platform (Balakrishnan et al., 2024).

Financial Costs have been recognized as a significant predictor of consumers' adoption intentions across different contexts (Twum et al., 2022). This research confirms the relevance of Financial Costs in adopting the metaverse as a marketplace for physical products (Mkedder and Das, 2024). In accordance with Ahmed (2022) and the survey conducted by VR Intelligence (2019), equipment costs seem to be a significant barrier for consumers. Therefore, to encourage adoption, consumers should be assured that the added value of the metaverse as a marketplace for physical products outweighs the expenses associated with purchasing equipment. Furthermore, it can be valuable to emphasize that metaverse equipment is not solely used for shopping purposes but can be leveraged for other use cases, such as attending virtual trips and events, gaming, or remote work (Mystakidis, 2022).

The finding that Trialability did not yield significant results raises important questions about the effectiveness of offering free trials as a strategy to reduce perceived risk and mitigate high costs, as suggested by Zhu and Chang (2014). One possible explanation for the contradicting finding could be related to the nature of the metaverse as a disruptive and complex innovation and the degree to which consumers feel they can adequately evaluate the metaverse as a marketplace for physical products through a simple trial (Mkedder and Das, 2024). To gain a deeper understanding of the relationship between Trialability and metaverse retailing adoption, further research is warranted. Future studies could explore the reasons for the insignificance and gain a deeper understanding of the construct's role in meta-

verse retailing adoption by using qualitative research methods, such as in-depth interviews or focus groups.

The unexpected finding regarding the lack of confirmation of the moderating role of Trust towards Meta in the study has significant implications for the understanding of consumer behavior and the metaverse. Several previous studies (Alsaad et al., 2017; Hamakhan, 2020) had suggested that trust in innovations and service providers would play a crucial role in shaping consumers' perceptions and behaviors. These studies implied that consumers' mistrust in Meta would act as a barrier due to potential privacy and data security concerns or issues. However, this study's results challenge this assumption, indicating that consumers may not have significant concerns about Meta's actions in the metaverse.

This unexpected finding might be attributed to several factors, such as consumers may prioritize alternative considerations, like the novelty and advantages of the metaverse, thereby diminishing the role of trust in their decision-making. Additionally, the company's successful rebranding from Facebook to Meta may have effectively disassociated it from past negative incidents concerning data privacy and cybersecurity (Mkedder and Das, 2024). Furthermore, it is possible that consumers lack comprehensive awareness of the privacy and security risks within this novel metaverse context (Mkedder et al., 2024b). Delving into these hypotheses and uncovering the underlying causes of this phenomenon necessitates further comprehensive research.

From a practical point of view, it is recommended that companies like Meta do not raise potential issues in their communications, as focusing on privacy concerns may inadvertently reinforce negative beliefs about the company and the metaverse (Sanderson, 2009). For instance, Gale et al. (2022) argues in their research that users struggle with overcoming cybersecurity because it represents a relatively unknown risk. On the other hand, Mkedder and Das (2024) finding raises several intriguing questions about consumer rights and protection in the context of emerging technologies and virtual environments. It is essential to consider whether consumers are sufficiently informed about the potential risks and challenges associated with the metaverse, suggesting a need for continued research in the area.

6 IMPLICATIONS

The outcomes of this study carry significant implications for corporate managers involved in developing and entering the metaverse marketplace. To increase metaverse retailing adoption among consumers, it is recommended that businesses, particularly in the technology and retail sectors, implement strategies aligned with the key drivers and barriers identified in this study. Marketing campaigns should emphasize the metaverse's Relative Advantage, Compatibility, Novelty, and Realism while addressing negative perceptions regarding the Complexity and Financial Costs of the metaverse as a marketplace for physical products.

Furthermore, it is advised that managers incorporate these attributes into their product development efforts, prioritizing user-friendliness, innovative features, and highly realistic interfaces. Exploring different pricing strategies is essential to ensure customers do not abstain from using the metaverse as a marketplace for physical products due to high equipment costs. Implementing flexible payment plans or subscription-based models that enhance affordability can help mitigate financial barriers and foster wider and more rapid adoption of the metaverse as a marketplace for physical products.

Additionally, retailers seeking to join the metaverse marketplace to offer their products do not need to fear potential negative spillover effects and harm on their brand reputation stemming from consumers' mistrust in the company Meta (Raufeisen et al., 2019). This finding has significant implications for partnering selection, indicating that companies do

not need to be concerned about co-branding with Meta. More specifically, it implies that businesses can be more open to collaborations with Meta without worrying about any adverse effects on their own brand image. This is particularly relevant in the context of the metaverse, where innovation and collaboration are essential for success. Businesses can tap into Meta's resources, expertise, and vast user base to enhance their presence within the metaverse, without the fear that any potential controversies or negative perceptions of Meta will harm their own brand. It allows businesses to harness the opportunities presented by the metaverse to the fullest extent.

By considering these practical implications, companies can position themselves effectively within the metaverse context and capitalize on the potential opportunities it presents as a marketplace for physical products. Employing these strategies can help companies gain a competitive edge, enhance customer satisfaction, and drive business growth in the evolving digital landscape.

From an academic perspective, a major contribution of this research is its pioneering use of a mixed-method research approach to investigate metaverse retailing adoption. The research findings demonstrate the ability to generalize qualitative insights through quantitative research. The exploratory sequential research design provides a comprehensive understanding of metaverse adoption in shopping for physical products, surpassing the limitations of relying solely on qualitative or quantitative methods.

The application of the DOIM revealed the significance of three innovation attributes – Relative Advantage, Compatibility, and Complexity. Even though only three out of five hypotheses were confirmed, this research reaffirms the generalizability of (some aspects of) the DOIM. Previous studies have consistently identified these three attributes as significant factors (Tornatzky and Klein, 1982). In contrast, Trialability often yields insignificant results, raising questions about its role in Innovation Adoption Theory (Kapoor et al., 2014). It is suggested that the factor may only have relevance in specific contexts, prompting a review and potential adjustment of Rogers' original DOIM. The qualitative study findings, which were subsequently validated in the quantitative phase, provide valuable insights into metaverse retailing adoption. The three constructs, Novelty, Realism, and Financial Costs, emerged as highly influential factors for consumers, underscoring their significance in researching metaverse technologies moving forward.

7 LIMITATIONS AND FUTURE PROSPECTS

The design of this research is subject to several limitations that open avenues for future exploration. One key limitation is the lack of specificity regarding the types of physical products evaluated in Study II. Although we aimed to cover a broad range of products commonly purchased online, the absence of detailed product categories might have introduced some variability in respondents' perceptions and attitudes. To mitigate this, we included a comprehensive definition of the metaverse and examples of physical products (e.g., clothes, furniture, consumer electronics) in the introduction of the questionnaire. However, future research should aim to specify product categories more clearly or investigate the influence of different product types on consumer intentions to adopt the metaverse as a marketplace.

Additionally, the qualitative study within this research suggested that the adoption of the metaverse and consumers' perceptions are likely to vary across different product types. Consequently, it would be beneficial to explore the role of product type as a potential moderator in future studies. By delving into specific product categories, future research could determine whether the observed effects become stronger or diminish under certain product conditions.

Another promising avenue for future research concerns the evolving nature of the metaverse. Changes in the interpretations among consumers may impact their perceptions and

the significance of factors over time. This means that the study's temporal validity is questionable, suggesting the need for ongoing research as the metaverse develops. Furthermore, the quantitative research data are limited to Dutch consumers, indicating a potential culture bias. In countries where the metaverse is less evolved, different results might occur and the perceptions and intentions of consumers might be lower. Therefore, future research is encouraged to include consumers from different countries to validate and expand upon the findings presented here or identify geographical differences.

Furthermore, nearly 90% of participants were between 18 and 23 years old, which limited the ability to interpret age effects, even though the metaverse is often viewed as an innovation tailored for younger consumers (Oxford Analytica, 2022). Future studies should aim to explore the metaverse's broader adoption by including participants from a more diverse age range. This approach could uncover how the significance of influencing factors varies across different age groups, or identify new drivers and barriers. Besides that, Generation Alpha, a promising target for the metaverse (McCrindle et al., 2021), was excluded due to the ethical complexities associated with researching minors. Future research could explore potential generational effects specific to these "digital natives" and thereby answer the question whether Generation Alpha exhibits distinct metaverse adoption patterns compared to other age groups, and what factors drive these differences. For instance, younger individuals may perceive complexity as a less significant factor due to their rapid acclimation to new technologies. Conversely, novelty could hold greater importance among Generation Alpha due to their innate curiosity and propensity for exploring novel experiences.

Certain limitations in the measurement scales were identified, including low Cronbach's alpha scores and items not loading onto intended scales. Future research should conduct a pretest of the questionnaire and review scales for clarity and data quality improvement. The nonconfirmation of the moderating role of Trust towards Meta and the unsatisfactory factor loadings of the trust scale suggest the need for further exploration of trust aspects and measurement refinements.

Especially with regard to the insignificances of Trialability and Trust towards Meta, it is advisable to pursue further research, specifically using qualitative research methods. This approach holds the potential to unveil the underlying reasons that have led to the unexpected findings of this research, which stand in contrast to prior research outcomes. This not only aids in making sense of the current results but also contributes to a deeper and more holistic understanding of consumer behavior in this rapidly evolving digital landscape.

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9 ANNEX

Construct	Items (measured on a 7-point Likert scale)	References
Perceived relative advantage	RA1: I think using the metaverse will enable me to shop physical products more quickly. RA2: I anticipate using the metaverse will make it easier for me to shop physical products. RA3: I believe using the metaverse will be a convenient way to shop physical products. RA4: Overall, I expect using the metaverse for shopping physical products will be advantageous.	Moore and Benbasat (1991), Ismail (2012), Jiang et al. (2021), Tan and Teo (2000)
Perceived compatibility	CA1: I anticipate shopping physical products in the metaverse will match my lifestyle. CA2: I think using the metaverse will fit well with the way I like to shop physical products. CA3: I believe using the metaverse will fit into my shopping style. CA4: I expect using the metaverse will work well with my current situation.	Moore and Benbasat (1991), Ismail (2012), Jiang et al. (2021), Tan and Teo (2000)
Perceived complexity	CX1: I believe that it will be challenging to use the metaverse to shop physical products. CX2: I think learning to use the metaverse to shop physical products will be frustrating. CX3: Overall, I believe that the metaverse will be difficult to use to shop physical products. CX4: I expect using the metaverse for shopping physical products will require a lot of mental effort.	Moore and Benbasat (1991), Ismail (2012), Jiang et al. (2021), Tan and Teo (2000)
Perceived trialability	TR1: I believe the metaverse will be available to me to adequately test shopping physical products. TR2: I anticipate having the opportunity to try the metaverse for shopping physical products. TR3: I expect to be able to use the metaverse on a trial basis long enough to see how to shop physical products. TR4: Before deciding whether to use the metaverse for shopping physical products, I think I will be able to properly try it out.	Moore and Benbasat (1991), Ismail (2012), Jiang et al. (2021), Tan and Teo (2000)

Perceived observability	OB1: I think that I would have no difficulty telling others about the result of using the metaverse to shop physical products. OB2: I believe I will be able to communicate to others the consequences of using the metaverse to shop physical products. OB3: I expect that I will see others using the metaverse to shop physical products. OB4: I anticipate that it will be easy for me to observe others using the metaverse to shop physical products.	Moore and Benbasat (1991), Ismail (2012), Jiang et al. (2021)
Trust towards Meta	TM1: I believe that Meta as a company would act in my best interest. TM2: The company Meta is interested in my well-being, not just its own. TM3: Meta as a company is truthful in its dealings with me. TM4: I would characterize the company Meta as honest. TM5: The company Meta is competent and effective in developing the metaverse. TM6: In general, Meta as a company is very knowledgeable about the metaverse.	McKnight et al. (2002)
Perceived realism	RE1: In comparison to the real world, I expect the metaverse to seem real. RE2: I think my shopping experience in the metaverse will be consistent with my real-world experience. RE3: I expect that the things that will be sold in the metaverse will look like things that are sold in real life. RE4: I anticipate that the metaverse shopping experience will be similar to in-store shopping experiences.	Daassi and Debbabi (2021)
Perceived financial costs	FC1: I think the equipment required to use the metaverse is expensive. FC2: There are financial barriers in the way of my using the metaverse. FC3: I think it costs a lot to start using the metaverse.	Twum et al. (2022)
Perceived novelty	NO1: I think using the metaverse to buy physical products will be a novel experience. NO2: I expect using the metaverse to buy physical products will be new and refreshing. NO3: I believe the metaverse represents a neat and novel way of shopping physical products.	Wells et al. (2010)
Intention to adopt	IA1: I intend to adopt the metaverse in the future. IA2: I intend to adopt the metaverse to buy physical products in the future. IA3: I intend to adopt the metaverse frequently in the future.	Taylor and Todd (1995), Rodríguez-del-Bosque and Herrero-Crespo (2011)

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(OUT)SMART THE PEER GROUP IN MARKET COMPARISON: BUILDING BUSINESS VALUATION MULTIPLES BY MACHINE LEARNING

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ABSTRACT

Traditionally, market comparison requires identifying a peer group, which still poses unresolved practical difficulties today. This research seeks to provide valuable insights into the practicality, efficiency, and accuracy of machine learning in valuing a company. It employs a state-of-the-art machine learning technique, Gradient Boosting Decision Trees (GBDT), to predict the valuation multiple directly. A yearly dataset of U.S. public companies from 1980–2021 was used. The most common multiples (EV/EBITDA, EV/EBIT, P/E, and EV/Sales) were tested. The performance of GBDT was assessed against an industry-based method. GBDT consistently outperformed the alternative method with an average 24 percentage point decrease in the median average percentage error. The results support GBDT's potential as a supplementary tool in valuation practice.

KEY WORDS

market comparison method, Gradient Boosting Decision Trees, industry multiple, feature importance

JEL CODES

G12, G32

1 INTRODUCTION

The corporate value is the current net value of future payoffs, such as dividends or free cash flows. There are two principal strategies to approach the uncertainty of estimating a company's future payoffs. In a direct valuation, an appraiser estimates the future payoffs explicitly and in absolute terms, as opposed to a relative valuation, where the payoffs are derived from comparable firms in the capital market. In practice, the market comparison method is widely utilised due to its straightforward applicability, interpretability, and speed by which a valuation can be completed (Plenborg and Pimentel, 2016). A global survey performed by Pinto et al. (2019) among equity analysts demonstrated that most respondents (93%) use market comparison during the valuation process.

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The basic concept of the market comparison method comes down to the law of one price (Knudsen et al., 2017). In an efficient market, comparable firms (substitutes on the financial market) are expected to be priced similarly. Typically, market comparison involves four steps. First, a peer group with known firm values is selected. Second, a measure driving the value of the subject firm is identified (typically an accounting measure such as earnings, book value, or revenues). Third, a valuation multiple is built using the peer group from step one, with the firm value as the numerator and the value driver as the denominator. Finally, the valuation multiple is applied to the subject company's value driver to determine its firm value. This paper specifically focuses on how the benchmark is selected (steps one and three of the market comparison method), which is generally regarded as the critical aspect of the implementation (Plenborg and Pimentel, 2016).

Machine learning applications have gained prominence in various areas, including corporate finance (Sellhorn, 2020). Traditional methods often fail in performance compared to innovative machine learning applications (Ding et al., 2019; Alanis, 2022; Geertsema and Lu, 2023). The reason lies in the complexity, multicollinearity, and non-linearity of the financial relationships, making it challenging to capture the interactions using classical statistical models. On the contrary, the ability to handle such data is the advantage of machine learning. It benefits from a growing amount of data serving as input to models and advancements in computational techniques that facilitate the rapid development of machine learning and artificial intelligence models.

In this context, this study aims to explore the potential of state-of-the-art machine learning in enhancing market comparison valuations from the practitioners' point of view. For this objective, it applies a gradient boosting decision tree model to predict the most common valuation multiples (price-to-earnings, enterprise-value-to-EBIT, enterprise-value-to-EBITDA and enterprise-value-to-sales), broadly following the method by Geertsema and Lu (2023), who, however, primarily predicted a different set of valuation multiples, among other methodological differences. To investigate the superiority of machine learning prediction, the outcome is compared and interpreted in relation to an alternative model represented by the industry mean multiple in terms of the accuracy measured by error rates, R-squared and correlation, and the importance of input variables. The structure of this article is as follows. Section 2 presents an overview of the prior literature on the market comparison method and a brief theoretical introduction to the machine learning technique. Section 3 details the proposed research design and data used for the analysis. Section 4 summarises and discusses the results. Finally, Section 5 concludes with the study's key findings and discusses the contribution of this research compared to Geertsema and Lu (2023).

2 THEORETICAL FRAMEWORK

2.1 Market Comparison Method

In theory, it is generally accepted that the subject company and its peer group are comparable when their value drivers, especially profitability, risk, and growth rate, are alike (Damodaran, 2002). However, there is no consensus on how to ensure this in practice. Plenborg and Pimentel (2016) differentiated three approaches to peer group selection: (i) industry-based, (ii) fundamental, and (iii) innovative approaches.

The prevailing practice is that the peer group is often selected solely based on affiliation to the same industry. Previous academic research has accepted the industry-based approach to selecting comparable companies (Alford, 1992; Cheng and McNamara, 2000; Liu et al., 2002; and in terms of the presented performance of the alternative models also Geertsema and Lu, 2023) advocating that industry affiliation means sharing similar market characteristics and thus the expected future performance.

Representatives of the fundamental approach argue that sharing similar market characteristics does not stipulate comparability of economic fundamentals (Bhojraj and Lee, 2002; An et al., 2010). They point out limitations of the industry classification, such as the lack of a universal classification system. Bhojraj et al. (2003) conducted a study comparing four different established industry classification systems: SIC (Standard Industrial Classification), NAICS (North American Industry Classification System), GICS (Global Industry Classification Standard), and the Fama and French classification. Based on their research, the GICS classification provided the most accurate explanation of the cross-sectional variability in valuation multiples and other financial indicators (Bhojraj et al., 2003). Additionally, they highlight that the GICS matches the different classification systems only 56% of the time, increasing the importance of choosing the industry classification system. Another reason for the potential inaccuracy of traditional industry classification systems is that new business areas are created during the dynamic development of the economy (Hoberg and Phillips, 2010, 2016).

On the other hand, a handpicked peer group based on shared fundamentals increases the risks of potential bias in peer selection, as demonstrated by the research of De Franco et al. (2015). Therefore, researchers attempted to develop a systematic technique to mitigate the subjective judgment needed for the fundamental approach – such as the warranted multiple by Bhojraj and Lee (2002); and An et al. (2010) or the sum of rank differences by Knudsen et al. (2017). These techniques are primarily based on statistical methods, which usually require the input data to have specific statistical properties (such as homoscedasticity), which financial data often do not fulfil. Moreover, with an increasing number of (independently distributed) fundamentals considered for selection, the size of the intersection of the most comparable firms in all fundamentals decreases rapidly (Alford, 1992).

The third approach is a mix of innovative techniques, such as using the co-searches on the EDGAR website by the U.S. Securities and Exchange Commission by Lee et al. (2015) or the similarity of business descriptions in annual reports analysed by Hoberg and Phillips (2010, 2016) with the use of machine learning. Generally, these approaches profit from big data availability and attempt to offer an objective peer group selection process.

2.2 Machine Learning Approach

Machine learning (ML) encompasses mathematical algorithms at the intersection of artificial intelligence and statistical models. ML detects patterns in structured and unstructured input data without being a priori given hypotheses about these mutual relationships (thus, a non-parametric model). Generally, these algorithms are used for clustering and dimensionality reduction on one hand (unsupervised ML) and for regression and classification tasks on the other hand (supervised ML). Predicting the valuation multiple is a regression task since the aim is to predict a continuous variable (target). Machine learning algorithms are data-driven models. Thus, they are distribution-free and do not require imposing any statistical properties on the input data, which is a significant benefit over any fundamental approach to peer group selection using statistical tools while maintaining objectivity. There is a growing body of machine learning applications in finance (Sellhorn, 2020), with many demonstrating excellent results.

In the market comparison method, emerging machine learning applications can achieve the needed trade-off between objectivity and flexibility due to their non-parametric nature. Our research references the work by Ding et al. (2019), Alanis (2022), and Geertsema and Lu (2023). Ding et al. (2019) tested ML on peer group selection to detect financial anomalies, and Alanis (2022) used it for regression of the beta factor, bypassing peer group selection. Both studies demonstrate the superiority of the machine learning approach to the industry-based approach. From a current point of view, the particular machine learning method they used – supported vector machine and random forest in Ding et al. (2019) and Alanis (2022),

respectively – are somewhat overshadowed by more recent methods, particularly the Gradient boosting decision tree (GBDT) used by Geertsema and Lu (2023) to predict the valuation multiple for market comparison valuation and peer group identification.

GBDT is an ensemble model of decision trees widely used in many machine learning tasks. An ensemble model refers to a technique which builds and combines numerous simple models, sometimes called weak-learners (James et al., 2023), to achieve superior prediction accuracy compared to a single complex model. In the case of GBDT, the weak-learner models are single decision trees, and the particular ensemble technique is gradient boosting.

A decision tree is a hierarchical model that employs recursive binary splitting, well-suited to capturing complex and non-linear relationships within the data (James et al., 2023). At each decision node, where the tree branches divide, the target data are divided into two subsets to maximise homogeneity within each subset. This division is based on a selected input variable and its threshold value, leading to the highest homogeneity at each split.

Gradient boosting means that for each iteration, a new weak-learner (a single decision tree) is sequentially added to the existing ensemble of trees in a way that minimises the residual error (also called the negative gradient, hence the name of the model) of the previous iterations of the ensemble (James et al., 2023). In doing so, GBDT uses information from the previously grown trees and gradually learns the patterns in the input data with a lower tendency to learn the 'noise' among the data provided for learning (risk of overfitting). Each iteration is only responsible for an incremental improvement; that is, not even the last iteration of the weak-learner would represent the whole model.

The key benefits of GBDT are its accurate predictions, high efficiency, and relative ease of implementation. It requires very little to no pre-processing of the input data as it is robust to outliers in explanatory variables (features). Furthermore, it also implicitly handles missing data among the features. Lastly, the underlying tree-based approach makes it relatively easy to comprehend how the model was built. However, compared to single decision trees (the weak-learners), the higher accuracy of GBDT comes at the cost of aggravated interpretability, as it is not possible to summarise the GBDT model into a graphical representation of a decision tree because of the sequential nature of the ensemble. These considerations are important should practitioners adopt machine learning as a fully-fledged method.

2.3 Contribution and Aim

We would like to contribute to the pioneering literature on the ML approach to market comparison valuation, particularly the work of Geertsema and Lu (2023). They developed ML regression models for market-to-book value, enterprise-value-to-assets, and enterprise-value-to-sales valuation multiples. They then compared their performance with five valuation multiple estimation techniques derived from prior literature. They tested two industry-based approaches: (i) the harmonic mean of the SIC industry affiliation from Liu et al. (2002), and (ii) the mean of an alternative industry classification set up by Hoberg and Phillips (2010, 2016) based on similarities of business descriptions. The last three models represented the fundamental approach to market comparison valuation. These included (iii) a statistical regression model to estimate the so called warranted multiple first proposed by Bhojraj and Lee (2002). Finally, the studies by (iv) Bartram and Grinblatt (2018, as cited in Geertsema and Lu, 2023), and (v) Rhodes-Kropf et al. (2005, as cited in Geertsema and Lu, 2023), both estimated the equity value by a cross-sectional (i.e., fundamental) analysis directly, skipping the step of building the market multiple first or even selecting a peer group. The results of Geertsema and Lu (2023) unambiguously support the hypothesis about the superiority of ML valuation accuracy measured by out-of-sample valuation errors, R-squared values, and Pearson correlation coefficients. The ML models systematically generated more accurate valuations over the entire sample period (1980–2019) and across all firm subsamples.

Apart from the findings on ML's superiority, Geertsema and Lu's results can also be interpreted in relation to the peer group selection approach discussion described above. We find it noteworthy that none of the five traditional models can be identified as the best (non-ML) since the alternative models ranked differently in different performance metrics. Generally, the two industry-based models scored lower valuation errors. In contrast, the fundamental approach of Bhojraj and Lee (2002) scored better in correlation. These results lead us to conclude that the industry-based approach is not merely a lack of effort when building the valuation multiple. Instead, the industry-based approach has proven once again that in some contexts, it is well justified to apply it, as suggested by the unresolved academic discussion over the proper peer group selection process.

This study broadly adopts the methods used by Geertsema and Lu (2023) to test the performance of machine learning (ML) on market comparison valuation by utilising the ML algorithm and performance metrics. Nevertheless, we contribute to this line of research by altering some key assumptions relative to Geertsema and Lu (2023) to broaden the applicability of their conclusions and to add a more practitioner-oriented perspective. Specifically, our key modifications include changing the set of valuation multiples being predicted to those more commonly used and assessing the over/under-performance of GBDT using a previously untested benchmark method that also originates from practice. Further details of the comparison between this study and Geertsema and Lu's (2023) study are provided in the Discussion section, following the methodology described in the next section.

3 METHODOLOGY AND DATA

This study aims to investigate whether (and why) a machine learning approach can enhance market comparison valuation. Essentially the ML constructs the valuation multiples from fundamentals provided for learning, thus the proposed method represents the fundamental approach to market comparison valuation.

In line with the general evaluation framework of ML and the research of Geertsema and Lu (2023), we assessed the improvement of GBDT compared to an alternative method that provides the baseline for evaluation. To benchmark the GBDT, we selected a traditionally used industry-based approach to the market comparison method.

The following two subchapters elaborate in more detail on the GBDT model and the alternative model respectively.

3.1 Proposed Method: Gradient Boosting Decision Trees

This study utilises the LightGBM implementation of GBDT (gradient boosting decision trees) developed by Microsoft. GBDT is recognised as a state-of-the-art decision tree-based model, noted for its accuracy and ease of use (reasons are explained in the previous section). We opted for LightGBM to enhance comparability with Geertsema and Lu (2023), who also applied LightGBM.

The proposed method uses 52 fundamental variables (of a financial and nonfinancial nature, including the GICS industry classification) as the explanatory input variables (features). These were selected to be as comprehensive as possible and with consideration of the general availability of the data for most of the sample across all industries. GBDT then internally selects the most important features for the given task. Based on GBDT weighting, we picked a final collection of 25 features during the fine-tuning phase used in the final models and created 6 additional GICS industry-derived features during the modelling. The final decision on the size and selection of variables is made based on several analyses performed during the fine-tuning phase. These analyses include recursive feature elimination cross-validation on the number of features, feature importance,

Spearman's correlations between the features, and an expert assessment (since not all combinations could be tested experimentally). We include an overview of variables and targets in the Annex including comments on usage and source and summary statistics (Tab. 4).

Missing observations were only addressed for the target variable by removing the particular firm-year observation. In contrast, we retained observations with missing input variables, as the LightGBM algorithm can handle them automatically. Moreover, However, the conclusions remain unchanged when testing the GBDT, even when all observations with any missing input variable are dropped. Due to extreme values (outliers) of the target variables in the retrieved dataset, the bottom and top 10% of the target variable distribution were trimmed. This process also eliminated any negative value of the target variable, aligning with the method of Liu et al. (2007). While the features were not explicitly treated for outliers or missing values, many potential outliers among the features were unintentionally removed due to the trimming of the targets. We also considered alternative outlier control approaches, as discussed in more detail in the section Model performance with alterations.

All absolute monetary values (among features only) were indexed to the price level of 2021 by the GDP Price Deflator reported by the World Bank for the USA. This adjustment ensures the values are comparable and prevents bias in the cross-sectional analysis due to inflation. Logarithmisation of the target variable was tested but eventually not used as it did not improve accuracy.

No other data manipulations were required, as the tree-based model is robust to outliers (among features) and multicollinearity and does not necessitate any standardisation.

During the fine-tuning of the model, we noticed a strong influence on the number of iteration rounds (num_boost_round hyperparameter) of the GBDT. Empirically, we selected 10,000 iterations. To avoid overfitting, we enabled an early stopping criterion, which stops training if the model does not improve for 10 consecutive rounds. The effect of the num_boost_round hyperparameter is discussed in the section Model performance with alterations.

The loss functions to optimise the model's internal parameters in the training phase included the root-mean-square deviation (RMSE) and the mean absolute percentage error (MAPE). Other hyperparameters of the GBDT were maintained at their default values.

3.2 Alternative Method: Mean GICS Industry Multiple

The alternative method serves as a benchmark for the proposed method. For this purpose, we selected a traditional industry-based approach to the market comparison method using the 6-digit GICS Industry level (GICS Industry Code). We opted for the GICS industry code for several reasons. Firstly, Bhojraj et al. (2003) claimed it to be the most suitable classification system and level for valuation. Therefore, it is, in our view, the best representative of the industry-based approach to the market comparison method. Secondly, we regard it as an addition to the five other alternative methods already tested by Geertsema and Lu (2023), of which two were industry-based approaches. Lastly, unlike Geertsema and Lu (2023), we included the same industrial affiliation (GICS) as a feature in the GBDT model to better highlight the effect of the GBDT. As a result, the GICS industry classification is utilised in both the proposed and alternative methods in this study.

The prediction of the alternative method for a given firm-year observation is then the aggregated industry multiple. It is computed as a mean of the individual companies' multiples affiliated within the same GICS industry in a particular year. We also explored other common function arithmetic and harmonic means, as discussed in more detail in the section on Model performance with alterations.

For the alternative model, the same adjusted dataset is used for the GBDT (including trimming outliers and missing observations among the target variables). Thus, the input for the proposed and alternative methods in terms of

subjects, GICS industry affiliation and industry aggregated mean multiples is essentially the same.

3.3 Tested Valuation Multiples

Since the aim of this study is to provide relevant findings for both practitioners and academics, we focused on the high-profile multiples commonly used in appraisals: price to earnings (P/E); enterprise value to earnings before interest and tax (EV/EBIT); enterprise value to earnings before interest, tax, depreciation, and amortisation (EV/EBITDA); and enterprise value to sales (EV/Sales). See Plenborg and Pimentel (2016) for a review of academic discussion on the choice of the multiple.

We trained a separate GBDT model for each selected valuation multiple (target variable) for our analysis. We prioritised historical accounting data over forward-looking estimates to avoid a reduction in the sample size due to forecast data availability.

3.4 Data

Data are sourced from the Thomson Reuters Refinitiv Eikon database. The sample comprised the universe of all public companies headquartered in the USA traded from 1980 to 2021. The precise data retrieval setting is described in the Annex. Approximately 10 thousand unique companies meet the criteria.

To evaluate the proposed and alternative methods, we set aside a random split of 25% of the available observations (the remaining 75% were used to train the GBDT model and compute the industry multiple).

3.5 Performance Metrics

The performance of both the proposed and alternative models was assessed using several performance metrics comparing the actual (observed) target values with their predictions. The prediction of the proposed method results from the GBDT model trained for the given target. The prediction of the alternative model is the mean multiple of the train-set companies affiliated with the same GICS industry. For both methods, all performance evaluations are based on the test dataset (out-of-sample testing stipulated by ML theory; see James et al., 2023).

The accuracy was assessed primarily by the median absolute percentage error (MdAPE) and mean absolute percentage error (MAPE). To identify a systematic over- or underestimation (bias) of the target, the mean and median percentage errors are also reported (referred to as MPE and MdPE, respectively). The percentage error is a relative measure of how close the prediction is to the actual value of the target variable. Furthermore, for a more detailed comparison with the results of Geertsema and Lu (2023), we also present the R-squared (R^2) and Pearson correlation between the actual and predicted target values (ρ).

4 RESULTS

4.1 Model Performance

This study applies GBDT, an ML technique, to market comparison valuation to determine if it can achieve better accuracy of the valuation multiple than the alternative approach relying on the industrial classification (GICS), and to analyse the results in relation to previous studies.

Our assumption is that the ML would exhibit higher accuracy measured by error rates (MAPE, MdAPE, MPE, MdPE) and greater explanatory power measured by R-squared (R^2) and Pearson correlation (ρ).

The results in Tab. 1 indicate that the proposed (ML) model outperforms the alternative method in all metrics across all targeted valuation multiples. The following conclusions can be drawn:

- The errors of ML's market multiples are consistently smaller compared to the alternative model. The ML model's MdAPE (median absolute percentage error) is reduced by

Tab. 1: Performance measured by error rates, R-squared, and Pearson correlation for all models considered

	MdAPE	MAPE	MdPE	MPE	R^2	ρ
Proposed method, %						
EV/EBITDA (ML)	6%	17%	0%	6%	68%	82%
EV/EBIT (ML)	6%	16%	0%	6%	73%	86%
P/E (ML)	7%	18%	0%	7%	67%	82%
EV/Sales (ML)	8%	32%	0%	18%	80%	90%
Alternative method, %						
EV/EBITDA (GICS)	25%	32%	0%	7%	11%	39%
EV/EBIT (GICS)	26%	33%	0%	7%	14%	43%
P/E (GICS)	25%	33%	0%	7%	8%	37%
EV/Sales (GICS)	47%	77%	0%	36%	23%	52%
Improvement, p.p.						
EV/EBITDA	19	16	0	1	57	43
EV/EBIT	20	17	–	1	60	43
P/E	18	16	–	–	59	45
EV/Sales	39	44	–	17	57	37

Note: If the change in performance is a positive value, it is indicated as an improvement in percentage points (p.p.), "–" means no improvement, and "0" means an improvement rounded to 0.

an average of 24 p.p., and MAPE (mean absolute percentage error) is smaller by approximately 23 p.p.

- MdAPE is always smaller than MAPE. The distribution of prediction errors is positively skewed for both methods, indicating that most prediction errors are minor, with a few outlier errors. From a practical appraisal point of view, smaller errors are preferable to larger errors.
- MPE is always above zero. Positive values of MPE for both methods indicate a bias of predictions towards overvaluation. This inclination might be explained by the exclusion of negative targets from the dataset (see the Data and Methods section for reasoning). However, the MdPE remains zero, meaning the predictions' central tendency (the median) is unbiased.
- The superior precision of ML models is also evidenced by consistently higher coefficients of determination and correlation scores.
- Notably, the EV/Sales multiple consistently shows higher prediction errors across all metrics. This suggests that it is not a universally suitable valuation multiple for all industries and stages of a company's life cycle. This finding is consistent with Baker and Ruback (1999).

Fig. 1 analyses the performance of all models over time. For all valuation multiples, the MdAPE of the GICS industry models (grey lines) oscillated around a constant level. In contrast, the errors of the ML predictions (black lines) exhibited a decreasing trend, indicating that GBDT became more precise in recent predictions. This enhancement in GBDT's performance over time is likely attributable to the growing dataset available for prediction after the outlier removal, as illustrated by the clustered columns in Fig. 1. This reasoning is most evident in the high errors in the first years of the model period.

4.2 Feature Importance

Given the sequential nature of the GBDT, it is impossible to represent the model as a single decision tree. Each decision tree within the model serves the purpose of incrementally improving the error generated by the previous iteration runs. Only when combined do they constitute the final prediction of the target. The general solution is to view the importance of

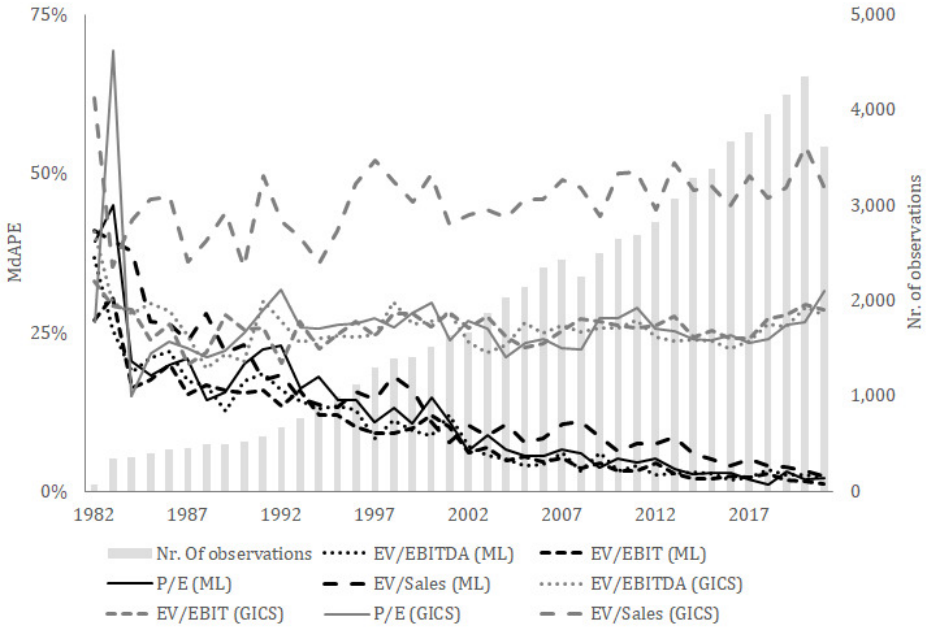

Fig. 1: MdAPE of the proposed method compared to the alternative method (primary axis) over time and number of observations (secondary axis) over time

each variable to illustrate the model's internal assumptions (James et al., 2023).

We present both the gain and split versions of the feature importance as computed by LightGBM during the modelling process. Gain importance measures the improvement in accuracy brought by a feature to the branches it is on, while split importance counts how frequently a feature is used to split data across all trees. We normalised both versions of the feature importance scores by dividing each score by the maximum score in the given target prediction model (separately for split and gain scores). This normalisation facilitates a more intuitive comparison across features. The following Fig. 2 shows both scores for each target (Panels B through E) and the gain score ranking across all scores (Panel A).

Fig. 2 reveals that the most significant feature contributing to increased accuracy is the mean industry multiple computed at the GICS Industry level (the same level used in the alternative industry multiple method). It ranks as the number one feature for all targets except for EV/Sales. Moreover, for EV/EBITDA and EV/EBIT, all other features contribute very little (less than 30%) when compared to the GICS Industry mean gain in importance. There are more significant features beyond the industry mean for the remaining targets. For P/E, an additional strongly contributing feature is the return on equity (ROE). For EV/Sales, the three most contributing features (in terms of gain importance) are Asset turnover, the mean GICS Industry multiple, and EBIT margin. The evidence of a more distributed importance across more key features with the industry mean being ranked only second explains why EV/Sales scored significantly higher errors in the alternative method, as presented in Tab. 1.

However, the low split importance of the mean GICS Industry multiple indicates that the GBDT model does not use it frequently – it actually ranks only in the 17th percentile or 27th out of 31 features in terms of the split importance scores summed across all targets. In contrast, the most frequent feature overall is the ratio of Property, plant, and equipment (PPE) net to PPE gross, indicating accounting obsolescence of the PPE (100th percentile).

We can summarise the findings on the industry multiple as follows: The gain in importance

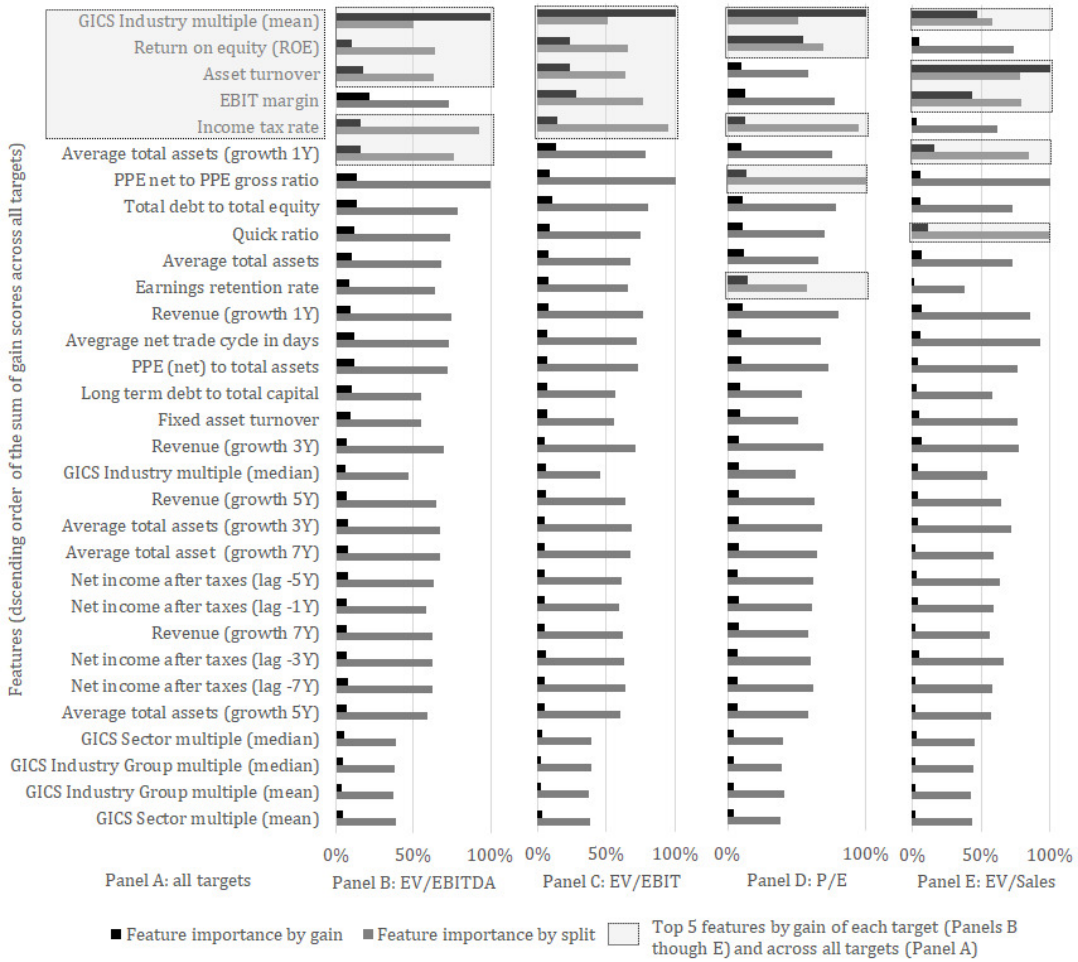

Fig. 2: Feature importance by gain and split for all target variables, expressed as a percentage of the maximum score for the given target. Labels in Panel A are in descending order based on the sum of the absolute gain importance scores across all targets. The top 5 most important features by gain score are highlighted with dotted squares for each target (Panels B through E) and across all targets (Panel A).

suggests that the industry multiple captures a significant portion of the target's variability (except EV/Sales), consistent with the common practice of leveraging the industry affiliation for benchmarking and the research supporting the use of industry multiples discussed above. Furthermore, while the industry multiple is crucial for GBDT to make a prediction, it likely serves as a starting point. It is evidently less utilised during the later iteration runs when the GBDT seeks finer interconnections within the data and refines the prediction. This nuanced data exploration is the added value of GBDT, contributing to its superior accuracy.

Given that the mean GICS Industry multiple is leveraged by the GBDT, all other GICS multiples are ranked as relatively insignificant both in gain and split importance. Any other industry level would merely duplicate the same information as the GICS Industry, which represents the most detailed level allowed in the model. Additionally, we note the GBDT's preference for the mean aggregation. For a discussion of mean versus median aggregation, please refer to the following section, Construction of the industry multiple.

4.3 Model Performance with Alterations

4.3.1 Alternative Outlier Control Methods

The control for outliers is the sole data cleansing procedure we implemented. We analysed the sensitivity of the performance metrics to changes in the definition of an outlier as the bottom and the top 1%, 5%, 10% (the primary configuration in this study), and 20% of the target variable.

As depicted in Panel A of Fig. 3, prediction errors produced by GBDT (black lines) consistently outperform GICS industry multiples when subjected to varying degrees of outlier control. Our findings indicate that the extreme values of the target variable are difficult to predict by both the ML and the GICS industry multiples (grey lines). By implementing stringent outlier controls to ensure data homogeneity the error is reduced substantially. However, when data size is excessively pruned – evident at the 20% data exclusion threshold – industry multiples exhibit a rise in error rate. This implies a critical threshold below which the data set no longer provides sufficient observations to construct a representative industry multiple. On the contrary, GBDT exhibits a lower sensitivity to such (subjective) data sample manipulation.

The pronounced advantage of GBDT is further supported by the Pearson correlation coefficients presented in Panel B of Fig. 3. The disparity between the ML approach and the conventional industry methodology is particularly pronounced at the intermediate data exclusion thresholds (5% and 10%). At the 20% threshold, where data homogeneity is highest, the correlation decreases slightly for GBDT (even as the prediction error continues to improve). In contrast, for industry multiples, the trend is reversed (simultaneous improvement of the correlation coefficient and worsening prediction error). This inverse relationship may indicate an overly homogeneous data set that offers limited learning potential due to its lack of diversity.

4.3.2 Number of Iteration Rounds

The number of boosting iterations represents the number of trees and is an important hyperparameter of the GBDT (num_boost_round). Panels C and D of Fig. 3 compare outcomes for 100 (the default setting for GBDT), 1,000, 10,000 (the primary configuration in this study), and 100,000 iterations. Through empirical analysis, we determined the optimal number of iterations to be 10,000, as it provides an optimal trade-off between accuracy and computational efficiency. The early stopping criterion is satisfied shortly after the 100,000th iteration.

4.3.3 Construction of the Industry Multiple

The industry multiple (serving as the prediction of the alternative model and one of the features in the proposed model) is commonly aggregated using a median or arithmetic mean function for its simplicity of interpretation. Often, the median is preferred by practitioners thanks to its robustness to outliers. However, some academic research advocates for the use of harmonic mean (Baker and Ruback, 1999; Liu et al., 2002). We tested all three aggregation methods for the construction of the industry multiple.

Our analysis suggests that the aggregation method does not affect the conclusion of the superiority of the ML models. When comparing the aggregation functions for industry multiples, we observed a trend where the medians produce the lowest values of median errors (MdAPE, and MdPE), whereas the harmonic means result in the lowest mean errors (MAPE and MPE), and the arithmetic means deliver the highest explained variance (R^2) and correlation coefficient (ρ). There is no single optimal method; different aggregation functions perform better under different criteria.

The highest correlation was likely decisive for the GBDT model (where all aggregation methods were considered), as indicated by the strong feature importance score, particularly for the mean industry multiple (Fig. 2). These findings suggest that the mean works well in conjunction with other features as explanatory variables. However, the median or harmonic

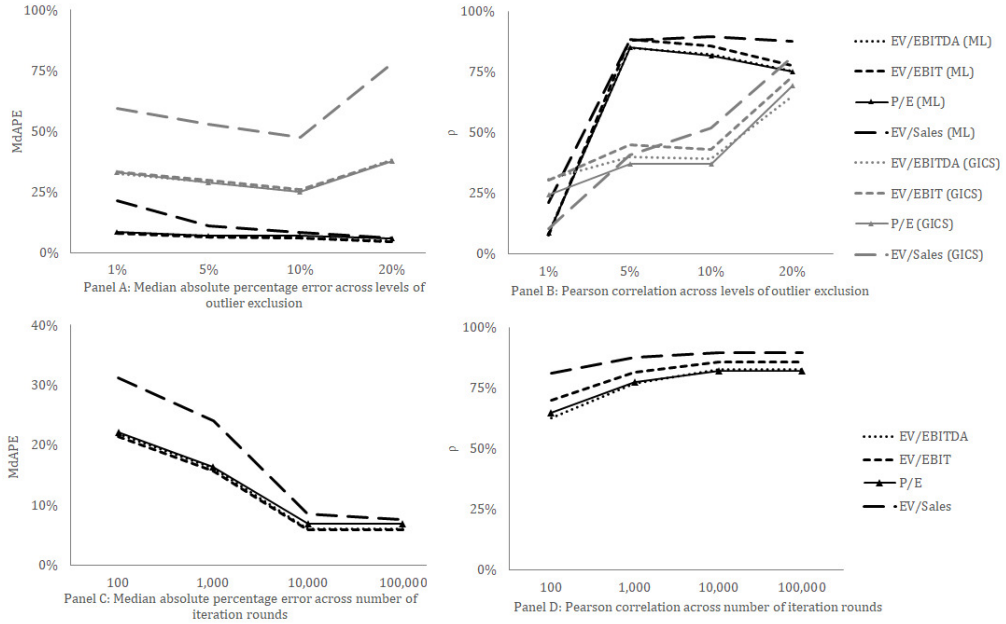

Fig. 3: Panel A and B: MdAPE and Pearson correlation under 1%, 5%, 10% and 20% trimming rule for outlier control. Panel C and D: MdAPE and Pearson correlation under increasing number of iterations rounds hyperparameter (sensitivity illustrated in Panels C and B is not relevant for GICS industry multiple).

Tab. 2: Results of the alternations of the alternative method using the median, (arithmetic) mean and harmonic mean for industry aggregation (GICS Industry level)

	MdAPE	**MAPE**	**MdPE**	**MPE**	R^2	ρ
EV/EBITDA median	**25%**	32%	**0%**	7%	11%	39%
EV/EBITDA mean	27%	36%	9%	16%	**16%**	**41%**
EV/EBITDA harmonic mean	25%	**30%**	−4%	**1%**	9%	40%
EV/EBIT median	**26%**	33%	**0%**	7%	14%	43%
EV/EBIT mean	28%	38%	9%	18%	**19%**	**45%**
EV/EBIT harmonic mean	26%	**31%**	−4%	**1%**	12%	44%
P/E median	**25%**	33%	**0%**	7%	8%	37%
P/E mean	28%	38%	10%	18%	**13%**	**39%**
P/E harmonic mean	26%	**31%**	−4%	**1%**	6%	37%
EV/Sales median	**47%**	77%	**0%**	36%	23%	52%
EV/Sales mean	57%	114%	33%	88%	**28%**	**54%**
EV/Sales harmonic mean	48%	**59%**	−19%	**3%**	8%	49%

Note: The best aggregation function is highlighted for each performance metric and valuation multiple. For the alternative method the median aggregation was used for comparability with the proposed method.

mean aggregation is a more precise choice for the industry multiple method. We chose median aggregation mainly because it is the more common choice among practitioners due to its intuitive explicability.

Additionally, we tested the sensitivity of the level of industry classification used for the prediction. Aggregating all companies together (i.e., disregarding the different industries) represents the most straightforward possible valuation approach. This global multiple method can be viewed as a baseline for evaluating any valuation model. We then compared the global multiple method with the industry multiple

method to contextualise the usefulness of the alternative method. The improvement from the simple global multiple to the industry multiple method (consistently using the second most detailed level of GICS classification) amounts to, on average, a 9 p.p. lower MdAPE and MAPE, which corresponds to a 21% (and 13%) improvement of the MdAPE (and MAPE, respectively,) relative to the global multiple. This significant improvement supports the common practice of using industry affiliation for benchmarking and the research supporting the use of industry multiples discussed above.

5 DISCUSSION AND CONCLUSIONS

5.1 Discussion

This research is closely related to the work of Geertsema and Lu (2023), further abbreviated as GL. In this section, we first summarise the aspects shared between these two studies. We list the key modifications representing our approach's contributing novelty, and finally, we discuss the differences in results, including identifying further minor differences in research designs.

This study and the GL study share the following:

- The objective is to enhance the market comparison method by implementing a machine learning algorithm (the GBDT).
- Research design where the ML model is benchmarked against the traditional alternative model(s) (however, the alternative model selection differs, as discussed below).
- A comparable dataset in terms of subjects (namely U.S. public companies of the past four decades; however, the frequency of the dataset differs, as discussed below).

The key modifications to GL's approach introduced by this study include:

- The valuation multiples assumed in the analyses differ. In this study, we predicted P/E, EV/EBIT, EV/EBITDA, and EV/Sales, which we selected because they represent the most common valuation multiples. In contrast, GL prioritised other selection criteria (availability and nonnegativity), and tested the market-to-book, enterprise-value-to-asset, and EV/Sales valuation multiples.
- To extend the variety of benchmark methods that serve to evaluate the performance of the proposed GBDT model, we introduced the mean industry multiple under the 6-digit GICS Industry level as the alternative method. GL tested five other alternative models, one of which represented an industry-based approach using an established industry affiliation system (SIC) and harmonic mean aggregation, while another used an alternative industry classification set up by Hoberg and Phillips (2010, 2016).

Tab. 3 compares the results of GL with results from this study for the proposed method (Panel A) and the alternative method (Panel B). In the first lines of each panel, in the squared brackets, we present the results as intervals ranging from the minimum value to the maximum value of the given metrics across all the targeted multiples. Next, we show the result of EV/Sales separately, which is the only target common to both studies under consideration.

The results in Tab. 3 indicate that both studies converge on the superiority of GBDT models over any alternative tested. A comparison of this study and the GL's (specifically the EV/Sales target) indicates that this study scores improved accuracy (lower errors). We attribute this improvement to the following factors (minor differences in the research design):

- The sample of GL consists of firm-month data (using quarterly accounting data). This study, however, utilises firm-year (with fiscal ends annual data), which likely contains less noise.
- GL trimmed the 10th percentile of selected accounting variables (book value, total assets value and sales) to exclude small firms. However, this study trimmed the lower

Tab. 3: Results of the proposed and alternative methods in this and the GL study. In Panel B, we emphasise the alternative method from the GL study which is the closest to this study (i.e., an industry-based approach using an established industry affiliation system). Squared brackets represent the interval of min. and max. values across all multiples.

	MdAPE	**MAPE**	**MdPE**	**MPE**	R^2	ρ
Panel A: Proposed method, %						
This study (ML), all multiples	[6%; 8%]	[16%; 32%]	[0%; 0%]	[6%; 18%]	[67%; 80%]	[82%; 90%]
GL study (ML), all multiples	[29%; 32%]	[48%; 59%]	[0%; 1%]	[19%; 28%]	[54%; 80%]	[89%; 90%]
EV/Sales (this study: ML)	8%	32%	0%	18%	80%	90%
EV/Sales (GL: ML)	32%	59%	1%	28%	80%	89%
Panel B: Alternative method, %						
This study (GICS, medians), all multiples	[25%; 47%]	[32%; 77%]	[0%; 0%]	[7%; 36%]	[8%; 23%]	[37%; 52%]
GL study (SIC, harm. mean), all multiples	[42%; 64%]	[58%; 129%]	[−35%; −15%]	[0%; 12%]	[−3%; 2%]	[38%; 64%]
GL study (all methods), all multiples	[40%; 86%]	[58%; 384%]	[−35%; 60%]	[−158%; 130%]	[−157%; 83%]	[38%; 86%]
EV/Sales (this study: GICS, median)	47%	77%	0%	36%	23%	52%
EV/Sales (this study: GICS, harm. mean)	48%	59%	−19%	3%	8%	49%
EV/Sales (GL: SIC, harm. mean)	64%	129%	−35%	0%	−1%	38%

and the upper 10% of target variables to exclude outliers of the target variable. As demonstrated above, a reasonably cleaner dataset lead to better accuracy.

- The industry boundaries likely differ between studies as GL applied the Fama-French 49 industries classification for the ML method. We rather used the GICS (i.e. same as for the alternative approach). According to Bhojraj et al. (2003) the GICS is the most suitable industry classification for valuation purposes.

Other methodological differences, which appear not to impact the accuracy, include the following.

- GL sample amounted to 1.8 mil. observations. This study used 93k observations, which were sufficient for the training of outperforming models.
- GL included 97 features, while this study uses 31. This aligns with GL's findings that a high number of variables does not significantly enhance precision. They reported the accuracy improved only by 7 p.p. when they increased the number of input variables from 10 to 97 (Geertsema and Lu, 2023, pp. 348–349).
- To improve the information quality of the data, GL performed a logarithmical transformation of the target variables and commented that it is one of the main sources of improved accuracy of the GBDT (hence the selection of the targeted valuation multiples). Whereas this study inflated the absolute values to 2021 price level.

The main takeaway from this comparison is that GBDT consistently outperforms various alternative methods of market comparison valuation in independent studies.

Nevertheless, it is essential to acknowledge the limitations and challenges associated with this approach. The primary concern is the general perception of machine learning as a 'black box', which can hinder its acceptance and integration into valuation best practice. In spite of the fact that GBDT algorithm is based on decision trees, which are well interpretable, the higher complexity of GBDT comes at the price of losing a portion of this transparency and representability. Additionally, the scope of the data used in our study is restricted to publicly traded U.S. companies with positive market multiple values, which may limit the generalisability of our findings. Future research addressing these limitations (such as extending the geographical scope, and/or including private companies) could further validate the broader applicability.

Practically, we advocate for a balanced view where machine learning is seen as a supplementary, rather than a substitutive, tool to the common methodologies like the industry multiple method and multiples built from a handpicked peer group.

5.2 Conclusions

This article covers the topic of applying machine learning to market comparison valuation method. We aim to provide both academic and practitioner audiences with a perspective on the benefits of integrating machine learning within the traditional valuation framework.

We employed the GBDT (gradient boosting decision tree) model for estimating market multiples. The prediction accuracy was compared with the traditional approach of the mean industry multiple method, which represents common traditional practice. The research was conducted on a dataset of U.S. public companies from 1980 to 2021. We tested a set of high-profile multiples commonly used in appraisals: P/E, EV/EBIT, EV/EBITDA, and EV/Sales.

We found that GBDT significantly enhances the accuracy of market comparison valuations with an average decrease of 24 p.p. in the median average percentage error, and it does not rely on human judgment when developing the valuation multiples. The error reduction of GBDT is attributable to its ability to handle complex financial data and computational efficiency. The results support GBDT's potential as a supplementary tool in valuation practice.

Additionally, we provided insights into market comparison method discovered by the GBDT during the prediction process, which could benefit both academia and practitioners. Firstly, from the feature importance analysis we note that the industry multiple ranked as the most important source of accuracy gain (most pronounced by EV/EBIT and EV/EBITDA), confirming the importance of the industry classification in current practice, thus supporting the industry-based approach to market comparison. Secondly, from testing various aggregation functions for industry-based approaches (median, arithmetic mean and harmonic mean), we drew a conclusion that there is no single optimal method, contrary to the pursuit in the literature for a universally superior approach; different aggregation functions perform better under different criteria.

Upon comparative analysis with related research, we conclude that GBDT consistently outperforms traditional market comparison valuation methods across independent studies. Furthermore, we want to point out that even datasets of reasonable size – both in terms of the number of features and observations – can yield very good results.

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8 ANNEX

Data Retrieval Definition

The data analysed in the study were downloaded from the Thomson Reuters Refinitiv Eikon database: `https://eikon.refinitiv.com/login` under the license agreement granted to the Prague University of Economics and Business. The sample comprised the universe of all public companies headquartered in the USA. The sample was further refined as follows: Active and Inactive companies, Primary Issues only, Instrument Type limited to the Fully Paid Ordinary Shares and the Ordinary Shares. The sample period spans fiscal year ends from 1980 through 2021. There are 10 thousand companies meeting the above-mentioned criteria and 73k–93k firm-year observations (depending on the target variable) as of the date of the data retrieval in April 2022).

Based on discussions with Reuter's representatives, Reuter's definition of the universe of public companies excludes companies that were public during the sample period but have been delisted since. Status inactive relates solely to companies which seized to issue financials whatsoever. Thus, delisted and yet active companies were not included in the sample.

Tab. 4: Summary statistics of the variables considered in this study. All variables are displayed after pre-processing as described in the Proposed method section (features are displayed after pre-processing for the EV/Sales multiple). *N* refers to the number of observations. Columns p10–p90 show the respective percentiles

Item	Usage	Source	*N*	Mean	p10	p50	p90
Enterprise value to EBIT (EV/EBIT)	used as target and for a computed feature	TR.EVEBIT	62,121	14.86	7.40	12.71	25.93
Enterprise value to EBITDA (EV/EBITDA)	used as target and for a computed feature	TR.HistEnterpriseValueEBITDA	65,882	10.85	5.61	9.59	18.23
Enterprise value to sales (EV/Sales)	used as target and for a computed feature	R.HistEnterpriseValueRevenue	74,411	3.37	0.61	1.88	8.74
Price to earnings (P/E)	used as target and for a computed feature	TR.HistPE	58,072	20.30	10.27	17.49	34.97
Features pro EV/Sales:							
Asset turnover	used as feature	TR.AssetTurnover	73,426	1.07	0.21	0.82	1.92
Average net trade cycle in days	used as feature	TR.AvgNetTradeCycleDays	72,202	−47.74	−23.82	60.17	186.33
Average total asset (growth 7Y)	used as feature	computed	50,116	267.48	−0.36	0.55	4.74
Average total assets (in mil.)	used as feature and for a computed feature	TR.TotAssetsPeriodToPeriodAvg	73,605	7.32	0.02	0.65	11.43
Average total assets (growth 1Y)	used as feature	computed	72,277	3.40	−0.12	0.06	0.51
Average total assets (growth 3Y)	used as feature	computed	64,843	55.73	−0.26	0.21	1.79
Average total assets (growth 5Y)	used as feature	computed	57,262	129.57	−0.33	0.38	3.18
Current ratio	not used	TR.CurrentRatio	68,011	2.93	0.71	1.90	5.24
Earnings retention rate	used as feature	TR.EarningsRetentionRate	50,751	0.35	0.08	0.94	1.00
EBIT margin	used as feature	TR.EBITMarginPercent	74,411	−21.23	−45.45	8.45	28.26
EBITDA margin	not used	TR.EBITDAMarginPercent	74,411	−12.81	−35.86	13.03	39.62
Employees	not used	TR.EmployeesasalYrEndPeriodToPeriodAvg	59,763	11,508	51	1,605	22,916
Equity (in mil.)	not used; used for a computed feature	TR.TotalEquityAndMinorityInterest	74,299	2.29	0.00	0.29	4.23
Equity (growth 1Y)	not used	computed	73,466	11.18	−0.33	0.06	0.86
Equity (growth 3Y)	not used	computed	68,878	62.31	−0.56	0.22	2.89
Equity (growth 5Y)	not used	computed	61,364	93.44	−0.64	0.37	4.77
Equity (growth 7Y)	not used	computed	53,996	69.96	−0.67	0.53	6.76
Fixed asset turnover	used as feature	TR.FixedAssetTurnover	70,818	57.84	0.62	5.37	28.90
GICS Industry Group EV/Sales multiple (mean)	used as feature	computed	73,142	3.36	1.49	2.69	6.47
GICS Industry Group EV/Sales multiple (median)	used as feature	computed	73,142	2.48	0.99	1.86	4.87
GICS Industry EV/Sales multiple (mean)	used as feature	computed	73,102	3.35	1.23	2.71	6.25
GICS Industry EV/Sales multiple (median)	used as feature	computed	73,102	2.58	0.92	1.88	5.08
GICS Subindustry EV/Sales multiple (mean)	not used	computed	72,911	3.35	1.07	2.65	6.77
GICS Subindustry EV/Sales multiple (median)	not used	computed	72,911	2.67	0.85	1.88	5.33
GICS Sector EV/Sales multiple (mean)	used as feature	computed	73,147	3.36	1.66	2.93	5.86
GICS Sector EV/Sales multiple (median)	used as feature	computed	73,147	2.38	1.04	1.88	4.49
Income tax rate	used as feature	TR.IncomeTaxRatePct	50,547	23.62	0.00	31.58	42.02
Long term debt to total capital	used as feature	TR.LTDebtToTtlCapitalPct	72,192	38.80	0.00	24.14	68.17
Net income after taxes (in mil.)	used as feature	TR.NetIncomeAfterTaxes	74,406	0.32	−0.04	0.02	0.59
Net income after taxes (lag −1Y) (in mil.)	used as feature	computed	73,807	0.29	−0.04	0.02	0.54
Net income after taxes (lag −3Y) (in mil.)	used as feature	computed	70,883	0.27	−0.03	0.01	0.50
Net income after taxes (lag −5Y) (in mil.)	used as feature	computed	64,820	0.26	−0.03	0.01	0.47
Net income after taxes (lag −7Y) (in mil.)	used as feature	computed	57,578	0.25	−0.03	0.01	0.46
PPE (gross) (in mil.)	not used	TR.PptyPlantEqmntTtlGross	67,294	3.10	0.00	0.23	5.34
PPE (net) (in mil.)	used for a computed feature	TR.PropertyPlantEquipmentTotalNe	72,288	1.74	0.00	0.10	3.04
PPE (net) to total assets	used as feature	computed	71,589	0.27	0.03	0.17	0.70
PPE net to PPE gross ratio	used as feature	computed	67,035	0.00	0.28	0.53	0.82
PPE net (growth 1Y)	not used	computed	70,885	0.00	−0.20	0.03	0.71
PPE net (growth 3Y)	not used	computed	65,752	0.00	−0.36	0.21	2.71
PPE net (growth 5Y)	not used	computed	58,394	0.00	−0.45	0.37	4.60
PPE net (growth 7Y)	not used	computed	51,394	0.00	−0.51	0.51	6.59
Quick ratio	used as feature	TR.QuickRatio	68,011	2.41	0.48	1.40	4.41
Return on assets (ROA)	not used	TR.ROATotalAssetsPercent	73,664	−18.59	−32.20	3.67	14.78
Return on equity (ROE)	used as feature	TR.ReturnonAvgTotEqtyPctNetIncomeBeforeExtraItems	68,236	−13.40	−45.63	9.36	30.82
Revenue (in mil.)	used for a computed feature	TR.TotalRevenue OR TR.BankTotalRevenue	74,411	4.17	0.01	0.50	7.91
Revenue (growth 1Y)	used as feature	computed	73,147	14.39	−0.17	0.07	0.56
Revenue (growth 3Y)	used as feature	computed	69,235	114.92	−0.26	0.21	1.90
Revenue (growth 5Y)	used as feature	computed	63,195	203.48	−0.30	0.37	3.64
Revenue (growth 7Y)	used as feature	computed	56,050	168.36	−0.33	0.51	5.50
Total debt to total equity	used as feature	TR.TtlDebtToTtlEquityPct	68,571	235.34	0.00	43.36	224.67
Headquarters country	not used	TR.HeadquartersCountry	74,411	n/a	n/a	n/a	n/a
Research and development expense (in ths.)	not used	TR.ResearchAndDevelopment	29,726	258.17	0.83	23.32	340.26

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IMPROVING AUTOMATED CATEGORIZATION OF CUSTOMER REQUESTS WITH RECENT ADVANCES IN NATURAL LANGUAGE PROCESSING

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ABSTRACT

In this paper, we focus on the categorization of tickets in service desk systems. We employ modern neural network-based artificial intelligence methods to improve the performance of current systems and address typical problems in the domain. Special attention is paid to balancing the ticket categories, selecting a suitable representation of text data, and choosing a classification model. Based on experiments with two real-world datasets, we conclude that text preprocessing, balancing the ticket categories, and using the representations of texts based on fine-tuned transformers are crucial for building successful classifiers in this domain. Although we could not directly compare our work to other research the results demonstrate superior performance to similar works.

KEY WORDS

service desk systems, customer requests classification, transformer models, machine learning

JEL CODES

C89, L86

1 INTRODUCTION

Customer support is an activity that a company provides before, during, and after the sale of a service or product. It involves various forms to ensure customer satisfaction at any stage of the life cycle (Menken and Blokdijk, 2009). Similarly, users or employees might require support from IT or other staff to solve various issues related to their work (Al-Hawari and Barham, 2021). The support often has the form of a helpdesk or service desk, which provides a single point of contact with customers or users.

Requests are represented by so-called tickets that capture the whole interaction between a user and operator in the form of a conversation. Within the conversation, the user gradually specifies the problem and the operator responds

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to the user's messages by asking additional questions, providing solutions, or redirecting the request to the appropriate department. Once a ticket reaches a certain state where the operator has a sufficient amount of information, a solver is assigned to it.

Help desks often have a tiered structure in which the user's first contact with the operator is the most significant for the early identification of the problem and subsequent routing of the ticket to the correct department. However, to be able to correctly redirect a ticket, the operator needs to know, what the request relates to. Ticket classification thus belongs to the main challenges in service desk systems (Jäntti, 2012).

Papers discussing the categorization of tickets in help desk systems often rely on traditional approaches based on sparse text representations (Zangardi et al., 2023). The modern artificial intelligence methods and neural networks typical in natural language processing (Qiu et al., 2020; Singh et al., 2022) that enable achieving state-of-the-art performance in many tasks are not examined.

The goal of the paper is to apply new approaches from the field of natural language processing (NLP) to the problem of ticket classification and derive useful findings and recommendations that would enable improved classification performance of real help desk systems.

2 CURRENT STATE

Landsman (2015) points out that from the efficiency perspective, the help desk system must not distinguish too many categories (hundreds) and recommends using about 20 categories. Al-Hawari and Barham (2021), Paramesh et al. (2018), Parmar et al. (2018), Herzig et al. (2013), and Eichhorn (2020) also investigated less than 20 categories. We can conclude that assigning a ticket to a category is typically a single-label multiclass classification problem, which is one of the most common applications of machine learning.

Only determining the ticket category is not sufficient to build a high-quality automated system. According to Olson (2018), operator response time and request resolution time are also very important indicators, and therefore assigning the correct ticket category as soon as possible after creation is essential to minimize operator delays.

We can expect that some problems are much more common than others, which leads to an imbalanced distribution of ticket categories. This fact poses significant problems for machine learning algorithms, as a sufficient number of documents from all categories is needed to train a good classifier (Liu et al., 2009). This is also confirmed by Paramesh et al. (2018), Parmar et al. (2018), Al-Hawari and Barham (2021), and Eichhorn (2020).

Although the field of natural language processing has experienced significant breakthroughs in recent years, many papers and applications still use traditional methods for applying machine learning to textual data. Specifically, for the field of automatic categorization of customer requests, several papers from recent years use sparse text representations with minimal use of modern artificial intelligence methods and neural networks.

Parmar et al. (2018) used a sparse representation of documents using tf-idf with not very extensive preprocessing steps, mainly comprising cleaning the dataset from empty values. The authors used a very imbalanced dataset containing thousands of documents with twelve different categories, on which they tested a total of five different classifiers, namely Multinominal Naïve Bayes (MNB), Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN). The best results measured by accuracy were achieved with an SVM classifier reaching 63% of accuracy. Such a high error rate, however, means that the classifier is not very useful.

Paramesh et al. (2018) also used a sparse representation of documents using tf-idf. The authors applied extensive preprocessing to the input data to remove unwanted names, email addresses, phone numbers, etc. They also re-

moved stop words and used oversampling and subsampling to balance the classes. Afterward, they used the χ^2 test to filter words with small importance. Multiple classifiers were combined using Bagging, Boosting and Voting Ensemble to improve the predictions. The best results were achieved using the Bagged Decision Tree classifier with an accuracy of 92.04%.

Eichhorn (2020) used traditional methods with sparse document representation (tf-idf) as well. Data preprocessing consisted mainly of lemmatization and stop words and punctuation removal. Categories with less than 100 tickets were removed which reduced the number of categories from 13 to 8 and thus greatly simplified the classification. On the other hand, the ability to predict less frequent categories was lost. From eight tested classifiers, Logistic Regression performed the best with an accuracy of 85%.

Al-Hawari and Barham (2021) used a dataset consisting of 1,254 manually labeled tickets from 13 categories related to technical support. The text data was cleaned from HTML tags, punctuation, and special characters and transformed using Weka's StringToWordVector filter with default setting to a structured representation (tf-idf) and classical machine learning models (J48, NaiveBayes, DecisionTable, and SMO) were trained. During evaluation, an accuracy of 81.4% was achieved.

It is evident that traditional methods and algorithms for classifying customer requests are still very relevant for building a robust system. However, new approaches and representations that usually enable reaching state-of-the-art results in many domains have not been investigated in the domain of the classification of help desk tickets. To identify relevant aspects of the process, related research needs to be examined.

Zhong and Li (2019) focused on the categorization of transcripts of customer calls (over 9,000 documents and 4 distinct categories). They explored several approaches using textual representations with static word embeddings. It was found that pre-trained GloVe vectors Pennington et al. (2014) provided the best basis for building the system. The transcripts were preprocessed mainly with text-cleaning techniques. The authors used a convolutional neural network (CNN) to create a classifier and achieved an F1 score of 93%.

Opuchlich (2019) focused on the classification of tickets from an SAP database containing several million documents and over 4,000 categories falling into two main areas, namely IT and HR. The author focused on the comparison and eventual combination of traditional and modern approaches using sparse and dense vector representations of tickets, namely tf-idf and fastText (Bojanowski et al., 2017). The paper also focused on the impact of various preprocessing techniques such as stop word removal, lemmatization, and infrequent category removal. As a result of the analysis of the impact of preprocessing techniques, it was found that removing sparse categories had a minimal impact on the performance of the classifier. The author created a two-tier classifier to separate the HR and IT tickets first (an accuracy of 97.46%), and then separate classifiers were trained for each domain. Since the used dataset had a very high number of categories, the author decided to provide the five most likely predictions of the classifier, which significantly increased the accuracy of the aggregate system. At all classification levels, the classifier trained with the traditional approach produced slightly better results than fastText. However, when combining both using a voting ensemble, the accuracy increased by 2–3% to 81.4% for the IT classifier and 78.9% for the HR classifier.

None of the previously mentioned works, dealing with customer support, used the latest innovations in the field of NLP. For example, Minaee et al. (2021) compared various deep learning models for some of the most common NLP applications, including multi-class classification. In their document topic classification experiment, they used the DBpedia dataset containing over 600,000 documents and 14 distinct categories. The authors tested a total of 9 different models and all of them achieved very good F1-scores greater than 98%. Two best-performing models were based on $\text{BERT}_{\text{LARGE}}$ (Devlin et al., 2018). In the task of

categorizing the 127,000 news article summaries into four distinct categories, the transformer-based models also provided the best results.

Transformer-based models (Vaswani et al., 2017) changed the field of NLP several years ago. The most famous one, BERT (Bidirectional Encoder Representations from Transformers) uses several encoders stacked in several layers (Rogers et al., 2020). The model created its own vector representations (embeddings) of input tokens based on the context in which they occur. The tokens are created using the WordPiece algorithm that adds the most frequent combinations of characters to the vocabulary (Wu et al., 2016). BERT can process only a given number of tokens, typically 512, while special symbols [CLS] and [SEP] are added to the beginning and end of the input. BERT can be trained from scratch in the Masked Language Modeling and Next Sentence Prediction tasks or fine-tuned in a task like classification. Depending on the number of model parameters, $\text{BERT}_{\text{LARGE}}$ (340 mil.) or $\text{BERT}_{\text{BASE}}$ (110 mil.) are typically used. A smaller all-purpose model DistilBERT can after fine-tuning in a specific task achieve performance comparable to larger models much faster (Sanh et al., 2019). There also exist models adapted for specific languages, like SlavicBERT (Arkhipov et al., 2019) for Slavic languages.

3 DATA AND METHODS

3.1 Data

The first dataset contains mainly technical support requests written in Czech and comes from the internal helpdesk of ALVAO, a leading provider of help desk systems in the Czech Republic. The requests are stored in the form of tickets consisting of the title of a request and all messages within the conversation between the user and the operator. Each ticket also has a category that the user selects when creating the request.

Tab. 1: Distribution of tickets in categories for the examined datasets

	Number of tickets	
Category number	**ALVAO**	**Endava**
1	3,987	34,061
2	1,595	9,634
3	368	2,628
4	272	921
5	237	612
6	116	239
7	65	191
8	57	137
9		72
10		45
11		4
12		3
13		2

The dataset contains a total of around 6,700 unique tickets, which are divided into eight categories. The distribution of the categories can be found in Tab. 1. It is evident that the data is strongly imbalanced – the majority category contains about 60% of instances, while the three smallest categories account for less than 4% of instances in total.

Individual messages in a ticket take the form of an e-mail. This means that a reply contains a new message, plus the original message to which the reply refers. It is, therefore, necessary to remove any duplicate pieces of messages, together with various auxiliary structures, such as greetings, signatures, or attachments that contain no relevant information for a category determination and would only decrease the quality of structured representations of the messages. Based on the preliminary experiments, removing these parts has a crucial impact on the classification performance.

The request title is usually a short text containing about 50 characters on average and less than 150 characters in 99% of cases. This corresponds to about 30 or 63 tokens when using the SlavicBERT (Arkhipov et al., 2019) tokenizer. 99% of the introductory messages of all tickets were not longer than 1,051 characters (the average length was around 213 characters). This corresponds to 488 tokens, which still fall

below the maximum number of tokens (512) that SlavicBERT can process. When combining the request name and the text of the first message, 551 tokens are needed for 99% of the tickets, which may imply a slight loss of context in the message representation.

The second dataset is the Endava public dataset. It is a technical support dataset that was originally used by Microsoft for the purpose of creating a web service for the automatic categorization of English tickets within Microsoft Azure (Żak et al., 2021). Requests are stored in the form of tickets containing the title and message text. Only the first request messages are available, from which various auxiliary structures, email headers, stop words, non-alphanumeric characters, specific names, and other unwanted words are removed.

The titles of the requests have 23 characters on average and 99% of titles have less than 68 characters. The messages of 99% of tickets are not longer than 1,900 characters (the average length is 266 characters). This corresponds to 455 tokens, which is within the limits of $\text{BERT}_{\text{BASE}}$ (512 tokens).

The dataset contains almost 50,000 tickets in 13 anonymized categories. The dominant category contains over 70% of all tickets and the second most represented category accounts for almost 20% of all tickets. At the same time, five categories have less than 100 tickets. It is, therefore, clear that some data balancing techniques need to be used to improve the quality of the classifiers.

3.2 Experiments

The title and body of the messages were concatenated (with a dot in between) to use as much available information from a ticket as possible. The experiments investigated both the traditional sparse tf-idf representation and the representation relying on static and contextual embeddings.

To produce the sparse representation, the new line characters were replaced with a space, all non-alphanumeric characters and stop words were removed, and the texts were converted to lower-case in the ALVAO dataset. Lemmatization or using the word bi- or tri-grams did not bring any improvements. The tf-idf representation had almost 25,000 dimensions.

We used fastText as the language model with static embeddings. All messages were preprocessed in the same way as in the case of the tf-idf representation and were used to train the CBOW model with 300 dimensions. The embeddings of all the words from a message were averaged to obtain a representation of the ticket.

BERT (Devlin et al., 2018) was used as the model for creating contextual embeddings. We used SlavicBERT for Czech texts and $\text{BERT}_{\text{BASE}}$ for English texts. According to Sun et al. (2019), fine-tuning a model on the end task is often beneficial for the quality of the embeddings for the given task. Thus, models without and with fine-tuning were investigated.

The process of fine-tuning a BERT model involves the choice of the fine-tuning method and the data chosen. The pre-trained SlavicBERT was trained on the Masked Language Modeling and Next Sentence Prediction tasks like the original BERT. These two models thus cannot be used for ticket categorization without adding and retraining a classification head.

It is also possible to extract the embeddings of the last layer before the classification layer and use them to train a separate classifier. According to Choi et al. (2021), a document can be represented by either averaging or summing all token embeddings or by using a special [CLS] token placed at the start of each document as its representation.

We examined BERT as a model providing contextual embedding as follows:

- pre-trained embeddings from the last layer of the model (averaged and [CLS] token only) were extracted and used by a separate classifier,
- fine-tuned embeddings from the last model layer (averaged and [CLS] token only) were extracted and used by a separate classifier,
- a classification head using the CLS token from the last layer was added and trained on the classification task at the same time as the model.

3.2.1 Balancing the Datasets

Since the categories in both datasets were very imbalanced, various balancing techniques were explored. Aggarwal (2020) distinguishes two major approaches to balancing a dataset, namely undersampling of dominant categories and oversampling of minority categories. The SMOTE method (Chawla et al., 2022) is highlighted for oversampling, which produces synthetic samples after vectorizing the documents. To increase the number of instances from the minority classes, Coulombe (2018) recommends data augmentation using back-translation. The augmentation process consists of translating the text into another language and then translating it back into the original language of the input text. The idea behind this process is to replace some words with their synonyms or similar expressions as part of the machine translation. The result is thus a new synthetic text that is very similar to the original one.

In this work, we examined the impact of removing minority categories in the Endava dataset (three categories that contain 9 samples in total), random undersampling of dominant categories, random oversampling of minority categories (by duplicating some instances and using SMOTE), and the augmentation of minority categories by using back-translation utilizing the Microsoft Translator inside Azure.

To augment the ALVAO dataset, categories containing 150 or fewer tickets were augmented using English, French, and German. For augmenting the Endava dataset, categories containing 250 tickets or less were augmented using French, German, and Spanish. The same categories like during data augmentation were oversampled. In the end, the categories with less than 150 tickets were enlarged to have 250 tickets in the ALVAO dataset, and the categories with less than 250 tickets were enlarged to have 400 tickets in the Endava dataset. During undersampling, the sizes of the majority categories were decreased from 3,987 to 1,500, and from 1,595 to 1,000 tickets respectively in the ALVAO dataset. In the Endava dataset, the two majority categories were undersampled to 2,628 tickets to have the same number of tickets as the third biggest category.

3.3 Studied Classification Approaches

Several classifiers that proved to be successful for categorizing text data were examined. The implementation from the Scikit-learn library (Pedregosa et al., 2011) was used, except for XGBoost, which is implemented in a separate XGBoost library (Chen and Guestrin, 2016), and BERT implemented in the Simple Transformers library (Rajapakse, 2023), which is an extension to the Hugging Face Transformers library. Unless otherwise stated, classifiers were always trained with the default parameters of a given implementation. The examined classifiers include Gradient Boosted Tree (XGBoost), Support Vector Machine (SVM), Decision Tree, Multinominal Naïve Bayes (MNB), Logistic Regression, Random Forest, K-Nearest Neighbours (KNN) with $k = 3$, 4, and 5, Multilayer Perceptron (MLP) with three hidden layers and 100, 200, and 100 neurons in them, and BERT with a classification head (a linear layer on top of the pooled output from BERT, implemented as the BertForSequenceClassification method in the Transformers library by Hugging Face).

The separate classifiers were applied to all the text representations, i.e., tf-idf, fastText, and BERT embeddings. Classifiers that provided the best results, had their hyperparameters further optimized. The effect of combining the best-performing classifiers into a voting ensemble where the category with the most votes is picked was also investigated.

The data was split in the ratio of 85% for training and 15% for testing for all experiments except the experiments utilizing the full (not undersampled) Endava dataset, where the test data was first undersampled and a ratio of 96% for training and 4% for testing was used. Classification success was evaluated using a test dataset that was distinct from the one used for creating the model. Thus, the observed measures represent realistic expectations (Xu and Goodacre, 2018).

The quality of classifiers was measured by macro- and micro-averaged F1 scores (Goutte and Gausier, 2005).

4 RESULTS

Tab. 2 contains the F1 scores achieved for different combinations of classifiers, text data representations, and data balancing methods for the ALVAO dataset. No categories with very small numbers of instances existed and thus were not removed. Only the best results for each balancing method are presented. It is evident that data augmentation using back-translation brought the biggest improvement so it was further investigated. Separate classifiers also always outperformed BERT, although often used its embeddings as the input.

Tab. 3 contains the results achieved with different text representations with the augmented dataset. The representations based on the fine-tuned BERT embeddings occupy the top three positions.

Selected models (XGBoost and KNN classifiers using the CLS token of fine-tuned BERT and BERT with a classification head) were further optimized and combined in a voting ensemble. This improved the classification result expressed by the F1 score by no more than 1%, which is a negligible improvement, see Tab. 4.

Tab. 5 represents the effect of balancing the dataset Endava. The operations related to balancing were performed in the following order (corresponding to the table rows): undersampling, removing minority categories, and one of the techniques increasing the size of minority categories (i.e., oversampling and augmentation). Undersampling and removing minority categories improved the macro F1 score by almost 19%. The biggest improvement related

Tab. 2: Results achieved for different combinations of classifiers, text data representations, and data balancing methods for the ALVAO dataset

Balancing method	Representation	Classifier	Macro F1 score	Weighted F1 score
none	BERT fine-tuned, AVG	XGBoost	0.845	0.975
augmentation	BERT fine/tuned, CLS	XGBoost	0.864	0.977
oversampling	BERT fine-tuned, AVG	SVM	0.838	0.976
SMOTE	fastText	SVM	0.834	0.967
undersampling	BERT fine-tuned, AVG	KNN(3)	0.837	0.971

Tab. 3: Results achieved for text data representations with the augmented ALVAO dataset

Representation	Classifier	Macro F1 score	Weighted F1 score
BERT fine-tuned, CLS	XGBoost	0.864	0.977
BERT fine-tuned, AVG	XGBoost	0.855	0.975
BERT fine-tuned, CLS	KNN(3)	0.852	0.975
BERT fine-tuned	classifier head	0.846	0.973
fastText	SVM	0.824	0.971
BERT AVG	logistic regression	0.779	0.957
tf-idf	XGBoost	0.761	0.953
BERT, CLS	logistic regression	0.690	0.939

Tab. 4: Results achieved after hyperparameters tuning the ALVAO dataset

Representation	Classifier	Macro F1	Weighted F1	Accuracy
BERT (finetuned), CLS	XGBoost	0.869	0.976	0.976
BERT (finetuned), CLS, class. head	voting ensemble	0.866	0.976	0.976
BERT (finetuned)	classification head	0.857	0.975	0.975
BERT (finetuned), CLS	KNN(3)	0.852	0.975	0.975

Tab. 5: Results achieved for different combinations of classifiers, text data representations, and data balancing methods for the Endava dataset

Balancing method	Representation	Classifier	Macro F1 score	Weighted F1 score
none	BERT fine-tuned	MNB	0.473	0.751
undersampling	BERT fine/tuned	XGBoost	0.528	0.794
removing small categories	BERT fine-tuned, CLS	MLP	0.760	0.770
augmentation	BERT fine-tuned, CLS	XGBoost	0.702	0.790
oversampling	BERT fine-tuned, CLS	XGBoost	0.676	0.773
SMOTE	BERT fine-tuned, CLS	Random Forest	0.690	0.794

Tab. 6: Results achieved for text data representations with the augmented Endava dataset

Representation	Classifier	Macro F1 score	Weighted F1 score
BERT fine/tuned, CLS	XGBoost	0.702	0.790
BERT fine/tuned, CLS	Random Forest	0.670	0.793
BERT fine/tuned	classifier head	0.680	0.781
BERT fine/tuned, AVG	XGBoost	0.672	0.769
tf-idf	XGBoost	0.641	0.755
fastText	XGBoost	0.630	0.747
BERT, CLS	XGBoost	0.582	0.656
BERT, AVG	KNN(4)	0.577	0.632

Tab. 7: Results achieved after hyperparameters tuning the Endava dataset

Representation	Classifier	Macro F1	Weighted F1	Accuracy
BERT (finetuned), CLS, class. head	voting ensemble	0.703	0.787	0.790
BERT (finetuned), CLS	XGBoost	0.702	0.790	0.792
BERT (finetuned), CLS	random forest	0.700	0.784	0.787
BERT (finetuned)	classification head	0.693	0.780	0.783

to increasing the size of minority categories was brought by augmentation, similarly to the ALVAO dataset.

Tab. 6 shows the best results achieved with each text representation on the augmented dataset. The approaches using the fine-tuned BERT model provide relatively good results, while the approach using the CLS token of the tuned BERT model and the XGBoost classifier provided the best results. Approaches using the pre-trained BERT model provided the worst F1 scores (both macro and weighted).

After tuning the hyperparameters of the models, only a negligible improvement over the best results of unoptimized models was achieved. Similarly to the ALVAO dataset, classifiers using the CLS token of the fine-tuned BERT model were selected. This time, XGBoost, Random Forest, and BERT with a classification head were studied. For the Endava dataset, combining the fine-tuned classifiers into a voting ensemble achieved the best macro-averaged F1 score of 70.28%, see Tab. 7.

5 DISCUSSION

In the experiments, we demonstrated that modern text data representations enable achieving results better than the traditional approaches. It was also found that to effectively use the embeddings obtained by the BERT model, it is beneficial to fine-tune the model on the given task. Even though BERT's added classification head did not provide the best results, the embeddings of the last encoder of this fine-tuned model were crucial to achieving the best results.

As transformer models are pre-trained on large text corpora and requests in helpdesk systems are highly domain-specific, traditional methods often bring satisfactory performance too (Campese et al., 2022).

It was also found that balancing the classes in the dataset often helps to improve the quality of the classifier. For the ALVAO dataset, augmentation using machine translation had the greatest impact, while the other examined techniques slightly degraded the results in this case. On the other hand, for the Endava dataset, the balancing techniques had a much greater impact and without them, the classifier would be practically unusable. Of the three examined techniques for increasing the size of minority categories, augmentation using machine translation was the most effective.

Using the best-performing classifiers, a macro F1 score equal to 86.94%, a weighted F1 score equal to 97.60%, and an accuracy of 97.61% were achieved for the ALVAO dataset. For the Endava dataset, a macro F1 score of 70.3%, a weighted F1 score of 79%, and an accuracy of 79.2% were reached, see Tab. 4 and 7.

For the ALVAO dataset, the main problems were caused by only one minority category that was very similar to another one. If these two similar categories were merged, a much higher macro F1 score could be achieved.

Much worse results were provided by the classifiers working with the Endava dataset. Since the dataset is anonymized, it is difficult to analyze the causes of the problem. The classes were also very imbalanced, much more so than in the ALVAO dataset, and even the balancing techniques were not able to fully resolve this issue. Moreover, the textual data provided here was already aggressively preprocessed, which may have reduced the effectiveness of contextual embeddings. Although the resulting classification metrics are quite low, they are much higher than those of Żak et al. (2021) who provided this dataset.

Although it is not possible to directly compare the results with other research based on different datasets, comparisons can still provide interesting information. For example, if we compare the results from the experiments with the ALVAO dataset to the work of Eichhorn (2020) using traditional approaches and similar data containing eight categories, we can see that the best approach from this paper achieves a 12.61% higher accuracy.

6 CONCLUSIONS

In this paper, we focused on the categorization of tickets in service desk systems. We explored modern neural network-based artificial intelligence methods and compared them to traditional approaches to find the potential for improvement and to address typical problems in the domain.

We demonstrated that modern text data representations, especially those provided by fine-tuned transformer-based models, enabled achieving results significantly better than the traditional approaches described in the literature.

During experiments with two real-world datasets, we concluded that text preprocessing, balancing the ticket categories, and using the representations of texts based on fine-tuned transformers were crucial for achieving classifiers with satisfactory performance.

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EXAMINING THE IMPACT OF ORGANIZATIONAL AND CUSTOMERS' OPERANT RESOURCES ON WORD-OF-MOUTH IN PREVENTATIVE HEALTHCARE SERVICE: A COMPREHENSIVE ANALYSIS ON CHILDREN IMMUNIZATION

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ABSTRACT

According to the service-dominant logic, the customers always contribute their resources to service delivery. This study adopts the service-dominant logic approach to social marketing in the context of preventative healthcare services for children immunization and investigates the influence of organizational (administrative quality, technical quality, and interpersonal quality) and customer operant resources (cultural resources, physical resources, and social resources) on word-of-mouth. Hierarchical multiple regression was used to test our hypotheses and the evidence indicated that all three quality dimensions of organizational operant resources significantly predict word-of-mouth behavior. Conversely, among three types of customer operant resources, social resources significantly predict word-of-mouth. The study contributes empirical insights to services marketing theory, social marketing theory, and practice.

KEY WORDS

service-dominant logic, social marketing, word-of-mouth, preventative healthcare, children immunization

JEL CODES

M31, M38

1 INTRODUCTION

Social marketing is influential for consumer behavioral change and has been traditionally examined through the value chain concept, with consumers perceived as being passive recipients of value. Researchers traditionally adopted the marketing mix concept of 4P's for social causes arguing organizations solely create value for customers. As the field progressed beyond traditional approaches, increasing body of scholarly work directed their research towards value co-creation by viewing consumers amidst multiple actors play an active role in the

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social marketing domain (Domegan et al., 2013; French et al., 2017; Luca et al., 2016; Osborne, 2017; Zainuddin and Gordon, 2020; Zainuddin et al., 2013). This view is foundational in the service-dominant logic approach that has been popular since 2004 which changed the dynamics of how we view exchanges between multiple actors (Vargo and Lusch, 2004). This suggests that every exchange is a service-for-service and good is a service-provision medium. Goods are produced because there is a service (during production), goods are meant to provide service, and consumers earn a living by providing service to other organizations (or to same organization) to buy goods and services (masking service-for-service exchange network as barter system is not globally customary). This view further illustrates that service organizations providing services to customers without customers' participation cannot entirely create value. The Service-Dominant Logic approach has been adopted in social marketing research, particularly for services requiring consumer participation such as preventative healthcare services (Zainuddin et al., 2013). Consumers among multiple actors in the service eco-system contribute their resources by participating in service provision, and the notion that organizations solely create value gives limited insight into sources of value creation thus impeding impactful consumer research (Vargo, 2020). The purpose of preventative healthcare service is to screen consumers or immunize them against potential diseases, nationally or internationally. Behavioral change is sought through such programs that benefit society, for example, parents realizing that vaccination of children at an early age prevents potentially fatal or debilitating diseases. Service-dominant logic illustrates that customers are value co-creators which is true in children immunization because parents' participation as customers cannot be overlooked.

Veraciously, children's immunization is a preventative healthcare service that requires active consumer participation (Butt et al., 2020). Millions of children are still unimmunized during the scheduled routine immunization, despite cost-effective expanded immunization programs and better health strategies (Adnan et al., 2021). The low-income and developing countries of the world still account for a substantially high mortality rate either because children are not wholly immunized or they are partially immunized (Yunusa et al., 2021). According to 2021 survey, Pakistan ranked third with highest mortality rate of children under age 5 (United Nations Children's Fund, 2023) predominantly due to a lack of awareness about children immunization among parents and caregivers (Hussain et al., 2021). According to the Global Tuberculosis Report, 2023 by the WHO, Pakistan is among 30 high TB burden countries (World Health Organization, 2023). The recent official report about Pakistan indicates that the proportion of fully immunized children was 66 percent (NIPS and ICF, 2019), but still the goal of 95 percent immunization rate set by the world health organization has not been achieved (Shahid et al., 2023). This is a serious issue for developing countries like Pakistan (Butt et al., 2020; Riaz et al., 2018). Exploratory study conducted by Jinarong et al. (2023) indicated that word-of-mouth through relatives, neighbors, and volunteers is an effective source of information for parents and community regarding children's immunization. As word-of-mouth is instrumental in achieving social marketing goals of preventative health services in the long term, there is a need to investigate factors that predict positive word-of-mouth of vaccination services for children. Service-dominant logic a holistic view provides the conceptual lens for this study by allowing us to identify factors derived from operant resources, that affect word-of-mouth behavior (Hau, 2019; Zainuddin et al., 2013).

This study presents a framework elucidating word-of-mouth dynamics in preventative healthcare services, particularly focusing on customer behaviors regarding children's immunization. It investigates the influence of both organizational and customer factors on word-of-mouth perception. Consequently, this research contributes by investigating the effects of organizational and customer operant resources on word-of-mouth within the context of preventative healthcare services for chil-

dren's immunization. In order to achieve this objective, the study employs service quality dimensions – namely administrative quality (AQ), technical quality (TQ), and interpersonal quality (IQ) to signify organizational operant resources. Additionally, it incorporates cultural (CR), physical (PR), and social (SR) resources to represent customer operant resources.

2 LITERATURE REVIEW

2.1 Service-Dominant Logic View

Service-dominant-logic provides a unique perspective of exchanges taking place between actors of the societies and differentiates between the terms 'service' and 'services' (Lusch and Vargo, 2006; Vargo and Lusch, 2004; Vargo and Lusch, 2008). The plural term 'services' refers to either value-added services attached to goods such as the delivery of goods to consumers' location, or to a set of intangible, perishable, inseparable products such as healthcare service, consultation, or other services (Fisk et al., 1993). The singular term 'service' is the foundational premise for service-dominant logic and is defined as "the application of specialized skills and knowledge" (Vargo and Lusch, 2004). It is considered the fundamental unit for all exchanges between all actors (Vargo and Lusch, 2016). This argument holds true for all services and product-based industries because without the application of specialized skills, knowledge, and capabilities neither service can be provided nor goods be manufactured. Therefore, in service-dominant-logic literature, the application of knowledge, capabilities, and skills is the common ground for exchange, irrespective of the type of goods or services.

Moreover, the service-dominant-logic emphasizes operant over operand resources (Vargo and Lusch, 2017). Operand resources are tangible resources on which an action is performed to create an effect (e.g. raw material, or other tangibles), while operant resources are intangible resources such as knowledge, skills, capabilities, and technology deployed on operand or other operant resources (Constantin and Lusch, 1994; Vargo et al., 2020). Service-dominant-logic posits that its operant resources are the foundation for competitive advantages and strategic benefits for firms (Vargo and Lusch, 2017). Organizations strive for knowledge, skills, capabilities, technologies, etc. because their services do not carry value to customers without these aspects and raw materials do not turn into meaningful products to be consumed by consumers.

Value creation is not only an activity a firm or organization embeds in its products or services rather multiple actors are involved (Vargo and Lusch, 2016; Viglia et al., 2023; Wang and Kim, 2017). In support of this view Akaka and Vargo (2015) already had accentuated the role of multiple actors in value creation through exchange of operant resources among them. This proposition was widely accepted by marketing scholars notwithstanding Viglia et al. (2023) who meticulously scrutinized multi-stakeholder value cocreation in the service ecosystem. Consequently, this study embraces the contribution of customer as the main actor concomitant with the organization in service provision. In this study, organizational operant resources are the intangible inputs that add value to the customers' service experience in preventative healthcare. While customers' operant resources are the intangible inputs that parallel with inputs of organizational resources, add value to the customers' service experience, see also Zainuddin et al. (2013). However, do inputs of both organizational and customer operant resources predict word-of-mouth? This question was empirically analyzed in this study. This is where our study contributes to social marketing literature with a focus on preventative healthcare from children's immunization perspective.

2.2 Word-of-Mouth

Word-of-mouth is understood as an informal communication approach employed to dissemi-

nate recommendations or information from one person to another (Anderson, 1998; Westbrook, 1987). It is the practice of individuals communicating with others in their social circle. Leon and Choi (2020) emphasized that word-of-mouth tends to prevail if the organization has more satisfied customers. In a study conducted by Leon and Nakayama (2020), word-of-mouth was found to be influenced by the overall service quality perception of customers in the health insurance industry. In alignment with these studies, empirical evidence by Agyapong et al. (2018) indicated that patients who perceived high service quality are more likely to draw other customers to healthcare facility.

To promote vaccination uptake in the community, word-of-mouth tends to play crucial role (Ramkissoon, 2021). Kareklas et al. (2015) furnished evidence demonstrating that attitudes and behavioral intention towards vaccination were more influenced by word-of-mouth compared to public service announcement. This evidence was further acknowledged by Jose (2022) study where word-of-mouth was found one of the influential factors in adoption of vaccine. Attracting new customers from a social marketing perspective might be costly but recommendations through positive word-of-mouth can lay out a free platform to promote certain changes in behavior (Sadeh, 2017). Having in view the importance of word-of-mouth influence on behavioral aspect of the customers, this study proposes important predictors of word-of-mouth in children immunization strategy.

2.3 Organizational Operant Resources

Value in preventative healthcare service was found to be influenced by service quality indicators i.e. administrative, technical, and interpersonal quality (Zainuddin et al., 2013). Administrative quality is the most acceptable framework in the healthcare sector (Asif et al., 2019). In healthcare research in the Pakistani context, a significant relationship between both administrative and technical quality was found with patient satisfaction (Asif et al., 2019). Lu and Wu (2016) findings documented that patients who experienced higher technical quality are more inclined towards positive word-of-mouth and more likely to recommend the services to others. Fattahi et al. (2022) investigated the role of interpersonal quality in generating patient-perceived value and positive word-of-mouth in hospitals. They concluded that patients who perceived higher levels of interpersonal quality were more likely to engage in positive word-of-mouth communication about their hospital experiences. Ultimately, Dandis et al. (2022) found word-of-mouth significantly influenced by the three key aspects i.e. administration quality, interpersonal quality, and technical quality in university on-campus healthcare centers.

In general healthcare, a significant number of studies were based on Donabedian (1992) service quality dimensions (technical and interpersonal quality), Andaleeb (2001) service quality dimensions (reliability, empathy, confidence, and tangibles), or Zineldin (2006) service quality dimensions (technical, functional, infrastructural, interactional, and atmospheric quality). In preventative healthcare context, Dagger et al. (2007) service quality dimensions (administrative, technical, and interpersonal quality) were adopted by Zainuddin et al. (2013) as inputs of organizational resources abreast customer resources for breast cancer prevention strategies. We argue that organizational operant resources representing administrative, technical, and interpersonal quality also contextually fit as important factors in the children's immunization process to determine word-of-mouth intentions for several reasons. First, administrative quality determines how smoothly parents can get vaccination services for their children when they take a visit to the hospital or a vaccination center. Second, technical quality determines how technically sound the staff is. Vaccination by experienced staff may avoid hurting the child during the vaccination. Third, interpersonal quality makes parents more comfortable and confident while interacting with the staff. Therefore, these dimensions were adopted in this study from a social marketing perspective.

2.4 Customer Operant Resources

The study undertaken by Frempong et al. (2020) revealed the involvement of customer operant resources in word-of-mouth generation. Evidence from the Sarmah et al. (2018) investigation substantiated the relationship between customer operant resources and customer advocacy. According to the cultural resource-based theory of service-dominant logic, there are three types of customer-operant resources (Arnould et al., 2006). These resources are categorized into cultural resources, physical resources, and social resources.

Equally important, empirical support was found in the relationship between certain types of customer operant resources and service outcomes (Hau, 2019). The same study investigated the role of information and knowledge customers have (cultural resources) in the healthcare service process. A worthwhile contribution was found to service delivery by customers who were familiar and knowledgeable. Moreover positive relationship between the existing knowledge of patients and the degree of participation in the value creation was also evident. Thus, this paper acknowledges the significant role of specialized knowledge of parents (cultural resources) during children's vaccination, when integrates with staff's knowledge, may create positive experience for customers i.e. parents/caregivers.

Gallan et al. (2013) found a positive relationship between the patient's positivity and participation in service delivery which in turn improves service quality perception and ultimately creates satisfaction with the co-produced service experience. The level of positivity as it leads an individual to prepare for a difficult situation (Fredrickson et al., 2003) is related to self-efficacy. An analysis conducted by Frempong et al. (2020) uncovered positive relationship between self-efficacy and word-of-mouth. Parents with high self-efficacy would be less reluctant to go for their child's vaccination despite thoughts about possible repercussions that would act as bridge towards favorable service experience. While adding to the importance of social resources, Kang et al. (2010) found a significant influence of family members on patients' knowledge and the ability to cope with chronic disease. Mayberry and Osborn (2012) found that if there are family conflicts and non-support, it will lead customers towards poor adherence. Consistent with previous research, substantial dependability on family members was recognized when seeking healthcare (Sherman, 2019; Widayanti et al., 2020). Vaccination awareness among college students was also associated with family members in a study conducted in Beijing, China (Liu et al., 2020). Nonetheless, this study is focused on social operant resources that help and assist the parents of the child. Parents are directly or indirectly influenced by the social support from family, relatives, friends, etc. when a child is brought for vaccination. Apart from social circle, the most common example is the presence of both father and mother makes the vaccination and carrying of a child more manageable. Consequently, this collaboration overcomes obstacles toward a favorable service experience.

3 CONCEPTUAL FRAMEWORK

The conceptual framework (see Fig. 1) aims to identify the key drivers of word-of-mouth in preventative healthcare services, crucial for leveraging it as a potential long-term social marketing tool for behavioral change. Addressing key research gaps, it firstly fills the void of quantitative empirical studies elucidating word-of-mouth generation in this domain, thereby identifying factors influencing it. Secondly, it delves into the unexplored realm of multiple actors' roles in shaping word-of-mouth perceptions within social marketing preventative healthcare services. Specifically, it highlights the contributions of two pivotal actors i.e. Customers and Organizations, during the service-for-service exchange.

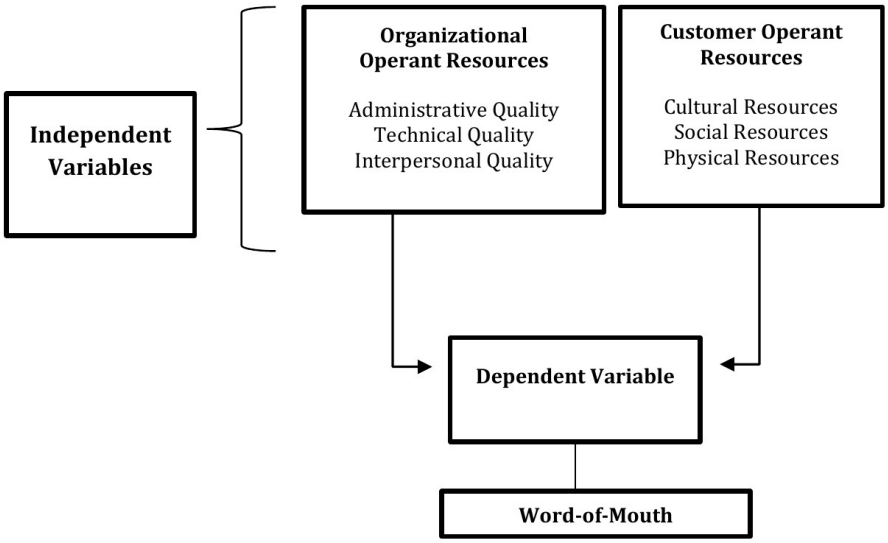

Fig. 1: Proposed Model of Organizational and Customer Operant Resources and Word-of-Mouth Behavior in Preventative Healthcare Service

3.1 Predictors of Word-of-Mouth in Preventative Healthcare Services

Administrative quality refers to processes that are facilitated by the systems of the organization (Dagger et al., 2007). Administrative quality encompasses administrative efficiency, support, service execution, and operations (Sony et al., 2023). It includes the aspects of a service organization that can smooth the path of core services which can add value to the service experience of the customer. Based on Abbasi-Moghaddam et al. (2019) study, administrative quality of hospital greatly influenced the positive perception of customers. This is hypothesized that the customer's experience with the administrative aspect of the organization during vaccination process would determine how customer engages in word-of-mouth, therefore:

H_1: *Administrative Quality (AQ) significantly predicts word-of-mouth in childhood immunization preventative healthcare services.*

Technical quality refers to the expertise of staff and other technical aspects like capabilities, competencies, proficiencies, qualifications, knowledge, or skills (Dagger et al., 2007). Technical quality of healthcare professional is responsible for better health outcomes except for cases where professional guidelines are violated (Currie and MacLeod, 2020). There is a high likelihood that parents during the vaccination of their child carefully evaluate the technical aspects of the staff. If the staff is experienced and effectively handles the vaccination process without hurting the child, then that may be the source of positive word-of-mouth therefore:

H_2: *Technical Quality (TQ) significantly predicts word-of-mouth in childhood immunization preventative healthcare services.*

Interpersonal quality refers to the relationship between service provider and customer that is interactive in nature and dyadic (Brady and Cronin, 2001). It includes the behavior, attitude, or manners of staff during interaction with the customers (Brady and Cronin, 2001). In preventative healthcare services, these aspects are responsible for the peace of mind and they have calming effect on customers (Kreuzer et al., 2020; Zainuddin et al., 2011). Additionally employee empathy positively influenced the trust level of customers on service provider (Bahadur et al., 2020). In this study we infer that interpersonal quality of customer-service provider interaction is the pre-dominant feature of the service, if favorably perceived by the customers; may serve as a basis for

recommending service to others through word-of-mouth. Therefore, the following hypothesis is formulated:

H_3: *Interpersonal Quality (IQ) significantly predicts word-of-mouth in childhood immunization preventative healthcare services.*

Customer cultural resources refer to the varying degrees and types of specialized knowledge, history, and imagination that customers orient themselves within (Arnould et al., 2006). Among these types, in healthcare generally (Hau, 2019) and preventative healthcare particularly, customers' knowledge of the procedure for health services is focused. Therefore, customer cultural resources are probed through the specialized knowledge of customers which might be a significant influencer during customer-service provider interaction. This type of specialized knowledge will thus act as a proxy for cultural resources (Hau, 2019). The more specialized knowledge of the customer, the more is the possibility that the customer will share relevant information with the service provider. Therefore cultural resources (specialized knowledge) would make customers active participants in service provision (Frempong et al., 2020). When a customer is knowledgeable about the procedure and disease, the knowledge gap between the customer and the staff is reduced, as a result the interaction becomes more effective (Hau, 2019). Therefore, the customer is more likely to indulge in positive word-of-mouth due to effective interaction which makes the encounter constructively meaningful; that is why this study anticipates the following hypothesis:

H_4: *Cultural Resources (CR) significantly predict word-of-mouth in childhood immunization preventative healthcare services.*

Social resources refer to the support that individuals gain from family, friends, and community on the other hand at a large scale (Arnould et al., 2006). These operant resources in social marketing play a pivotal role in encouraging an individual to adopt certain enduring behaviors. Unfolding evidence also indicates that social resources have been critical antecedent of preventative behaviors among population (Jetten et al., 2020; Stickley et al., 2021). Therefore, the customer with more social resources (assistance or support from family, friends, relatives, etc.) is likely to indulge in positive word-of-mouth as a consequence of benefits that the customer secured on account of support from family and relatives during the service encounter. That is to say the gap caused by lack of support during service encounter is filled by social resources. Based on this, the following hypothesis is predicted:

H_5: *Social resources (SR) significantly predict word-of-mouth in childhood immunization preventative healthcare services.*

Physical resources are defined in terms of the strength or capability of an individual, emotions, and energy an individual possesses (Arnould et al., 2006). For that reason, self-efficacy will be more suited as a proxy for physical resources (Hau, 2019). Self-efficacy is thought of as the individual capability to perform complex acts (Schwarzer et al., 1997). It is posited that self-efficacy explains the individual's perception of him or herself about the control he or she has over the action, which motivates the individual towards the enduring effort (Schwarzer et al., 1997). It is believed that self-efficacy guides the intention of an individual to initiate certain behaviors and continue them despite hardships or barriers (Farley, 2020). A Plethora of evidence suggests positive relationship between self-efficacy and engagement in preventative healthcare behaviors (Tan et al., 2021). Therefore, customers with high self-belief in his or her coping abilities of health problems are more likely to become active participants in word-of-mouth promotion due to the judgment of having high confidence in one-self of abilities they possess. Therefore the following hypothesis is anticipated:

H_6: *Physical resources (PR) or self-efficacy significantly predicts word-of-mouth in childhood immunization preventative healthcare services.*

4 METHODOLOGY AND DATA

This study is based on a quantitative approach for empirical investigation and data collection frequency was cross-sectional. Data collection was based on the expanded program on immunization (`www.epi.gov.pk`) as this program is in execution by the government of Pakistan with the help of the United Nations International Children's Emergency Fund (UNICEF). Immunization vaccines are provided to children by this program to immunize children against potential diseases and disabilities through public or private hospitals and vaccination centers. A convenient sampling technique was used to recruit the sample for hierarchical multiple regression. The sample comprised parents or caregivers of children in Pakistan, who have taken their child under the age of 2 for vaccination, see also Fredrickson et al. (2004). In response to pandemic restrictions, the online study was conducted through circulating Google form link.

4.1 Sample Attributes

This immunization program has a complete course for parents to vaccinate their children after a certain age of a child, see also (Riaz et al., 2018). The population size is infinite, the minimum required sample size calculated was 123 ($n = 123$) through an online sample size calculator (Soper, 2015) for hierarchical multiple regression with an anticipated effect size = 0.15, desired statistical power level = 0.9, and probability level = 0.05 (Cohen et al., 2013; Cohen, 1988). 263 valid responses based on the more recent encounters with childhood vaccination were qualified for further analysis. This considerably exceeds the minimum sample size of $n = 123$ calculated for this study.

The geographical representation comprised provinces (or states) that make up the whole country (Pakistan). The highest number of responses were received from Khyber Pakhtunkhwa (31.56%), followed by Punjab (20.53%), Balochistan (17.87%), Sindh (11.79%), Gilgit Baltistan (6.46%), Azad Jammu Kashmir (6.08%), Islamabad or capital of Pakistan (5.70%). Among all responses, 69.58% constitute male respondents ($n = 183$), and 30.42% constitute female respondents ($n = 80$). Most of the respondents were educated or literate. Respondents were also asked about the place, which falls under city or village. 69.96% of respondents selected 'city' ($n = 184$) and 30.04% of respondents selected 'village' ($n = 79$).

4.2 Scale Development

The used questionnaire in the current research study stemmed from the established research studies on healthcare services and preventative healthcare services. However, a few modifications were incorporated to measure the specific parental experiences during the child vaccination procedure. More precisely how these procedures/experiences exhibiting various significant categories of organizational and customer operant resources structure the word-of-mouth perception? Each construct was assessed using a 5-point Likert scale, where a score of 5 indicated strong agreement and a score of 1 indicated strong disagreement. The questionnaire for organizational operant resources to measure administrative, technical, and interpersonal quality was adapted from Zainuddin et al.'s (2013) study. The mentioned study was grounded on preventative healthcare services and drew upon items from Dagger et al. (2007). The items of administrative quality reflected customers' perception of standard, performance, and trust in administration. The items related to technical quality reflected customers' impression of the standard and performance of core service (vaccination) received at healthcare centers during childhood vaccination. The items pertaining to interpersonal quality were based on the customers' perception of kind of interaction they had with the healthcare staff.

The measuring instrument for customer operant resources (including cultural, physical, and social resources) and word-of-mouth were adopted from Hau (2019) and developed to be

employed in healthcare settings. The items of cultural resources comprised customers' knowledge about the service procedure, knowledge about childhood immunization, and comprehension of instructions during the vaccination process. The items related to physical resources or self-efficacy were based on questions related to one's strength and coping abilities to health problems faced by his or her child. Items of social resources included questions related to the acquiring of assistance and knowledge or experience from relatives, friends, or colleagues. The questionnaire for word-of-mouth, originally from Hau (2019), was grounded on previous studies by Eisingerich et al. (2014) and Zeithaml et al. (1996). Items related to word-of-mouth encompassed the extent to which parents or caregivers will share their experience, share positive aspects of the service encounter, and recommendations to others. The questionnaires comprised close-ended items.

The questionnaire was first translated into the national language of Pakistan (Urdu), which is widely understood and spoken throughout the country by all ethnicities. For that purpose professional translator was hired. When the translated version was received, it was back-translated to English by a Ph.D. scholar to examine if the translated version best fits the earlier version of the questionnaire and necessary adjustments were made accordingly (Hambleton, 1993). Once the translated version was ready, ten potential respondents were interviewed to check if it was clearly comprehended by the respondents and the responses were altogether positive.

4.3 Hierarchical Multiple Regression

This study employed hierarchical multiple regression analysis using SPSS 26 to assess the predictive significance of organizational operant resources (administrative, technical, and interpersonal quality) and customer operant resources (cultural, social, and physical resources) in relation to word-of-mouth regarding children's immunization. The researchers validated the assumptions of hierarchical multiple regression analysis, confirming data adequacy.

To address common method bias, the correlation matrix approach (Bagozzi et al., 1991) was applied using SPSS 26, ensuring that the correlation between any two constructs was below 0.9 (Pavlou et al., 2007). The study found correlations consistently less than 0.9, indicating no significant common method bias. Additionally, Cronbach's alpha reliability tests confirmed internal consistency, with values falling within the acceptable range for a small number of items (van Griethuijsen et al., 2015), as values for administrative, technical, and interpersonal quality were: 0.854, 0.864, and 0.861 respectively; cultural, physical, and social resources were: 0.749, 0.735, and 0.679 respectively.

The requirement for linear relationships between each independent and dependent variable, as outlined by Osborne and Waters (2002), was examined in this study. The scatter plots below (see Fig. 2, 3, 4, 5, 6 and 7) clearly demonstrate the presence of such relationships, thus confirming our assumption.

Data must exhibit absence of Multicollinearity among independent variables, such that inter-construct correlation should be less than 0.9 (Franke, 2010), with tolerance levels exceeding 0.2, and variance inflation factors below 5. In this study, all tolerance levels exceed 0.2 and variance inflation factors are below 5, thus statistical tests indicate absence of Multicollinearity. Furthermore, residuals should demonstrate independence, typically reflected in a Durbin-Watson value close to 2. For this study, the Durbin-Watson statistic was 1.895, aligning with this expectation. Additionally, homoscedasticity, indicating consistent variance of residuals, was confirmed (see Fig. 8) by observing no discernible funneling in the plot of standardized residuals versus standardized predicted values, as suggested by Berry and Feldman (1985).

Another assumption pertains to the normal distribution of residuals' values (Cook and Weisberg, 1982). While the P-P plot indicates some deviation from normality (see Fig. 9), it is noteworthy that only extreme deviations are likely to significantly affect the results.

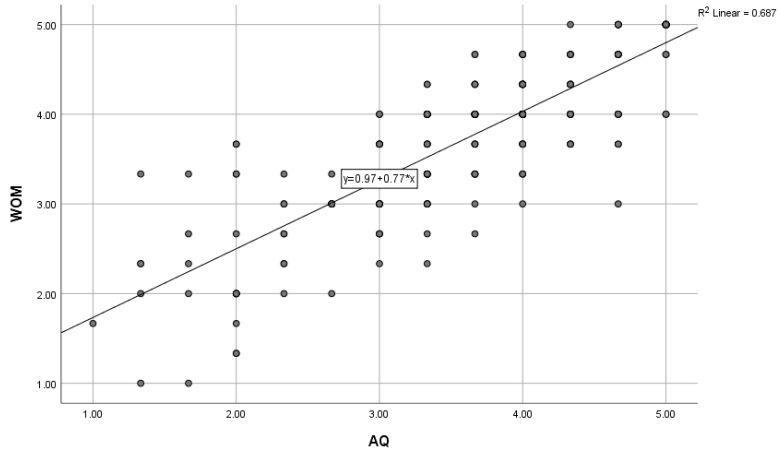

Fig. 2: Linear curve of Administrative quality (AQ) vs. Word-of-mouth (WOM)

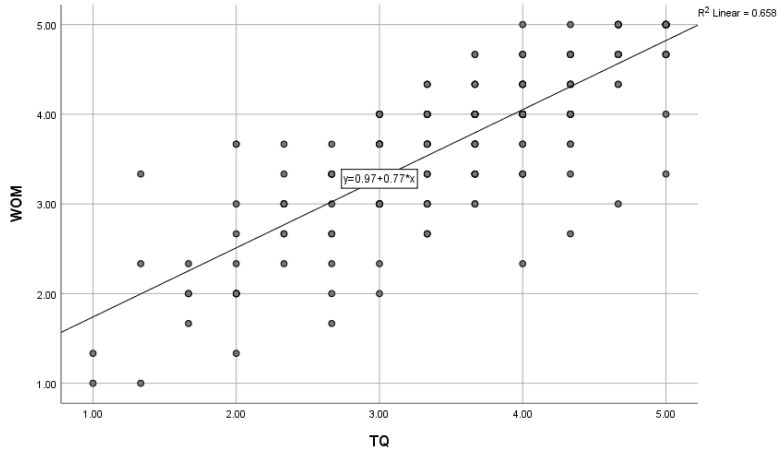

Fig. 3: Linear curve of Technical quality (TQ) vs. Word-of-mouth (WOM)

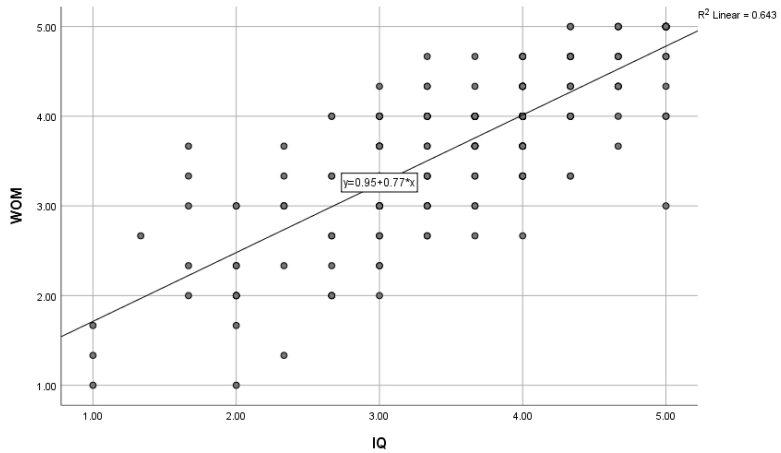

Fig. 4: Linear curve of Interpersonal quality (IQ) vs. Word-of-mouth (WOM)

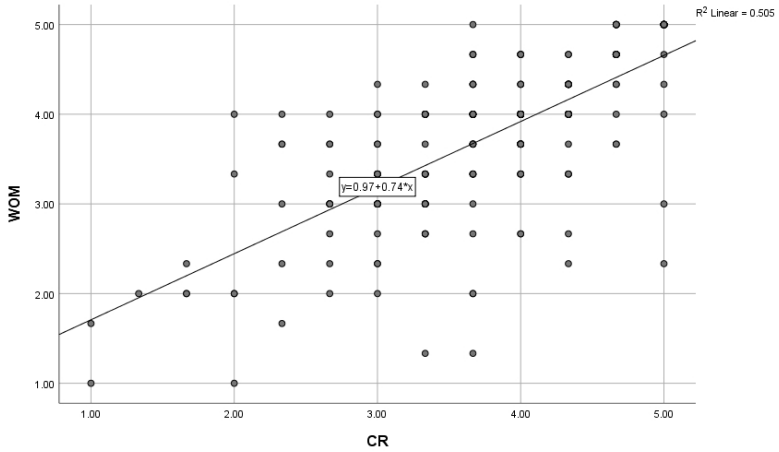

Fig. 5: Linear curve of Cultural Resource (CR) vs. Word-of-mouth (WOM)

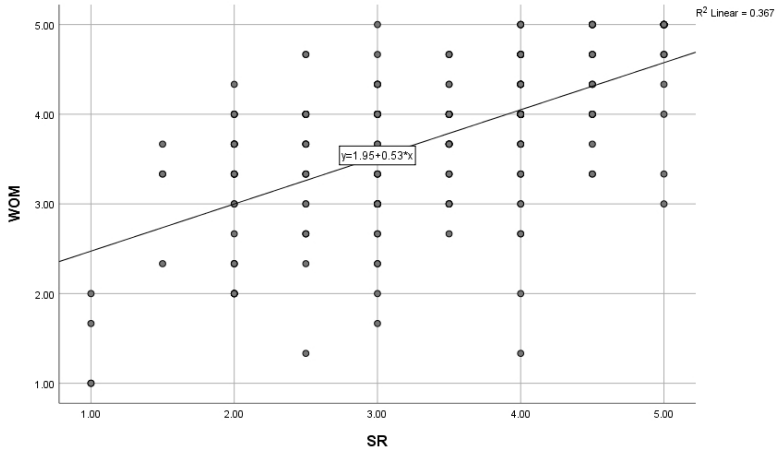

Fig. 6: Linear curve of Social Resources (SR) vs. Word-of-mouth (WOM)

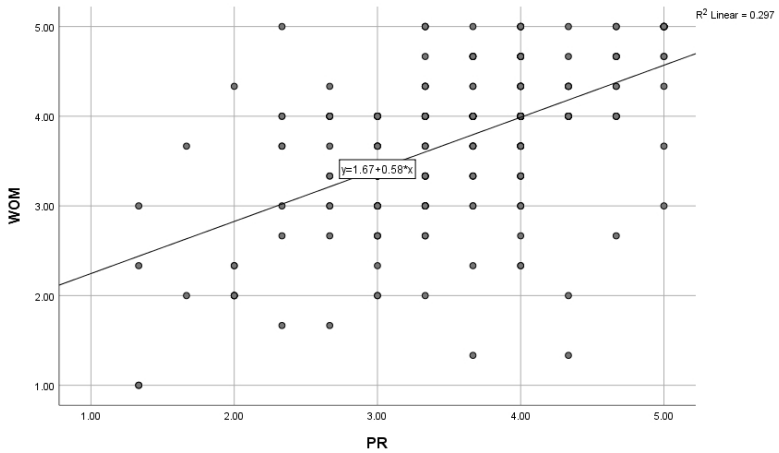

Fig. 7: Linear curve of Physical Resource or self-efficacy (PR) vs. Word-of-mouth (WOM)

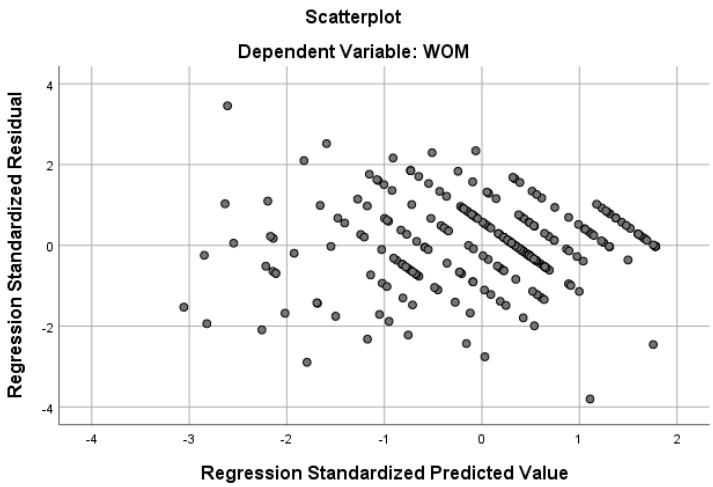

Fig. 8: Homoscedasticity

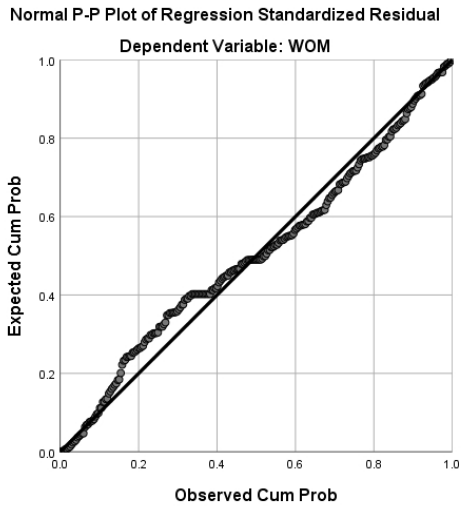

Fig. 9: Distribution of residuals' values

Therefore, the findings are deemed valid despite minor deviations.

The final assumption addresses potential bias from influential cases within the model. Results indicate that all Cooke's distance values were below 1, signifying that no individual cases exerted undue influence on the model (Cook and Weisberg, 1982).

5 RESULTS AND DISCUSSION

The study was organized to find out if various forms of operant resources can predict word-of-mouth. Therefore, it was hypothesized that administrative quality, technical quality, interpersonal quality, cultural resources, social resources, and physical resources were predicted to positively influence word-of-mouth. To test these anticipations, a hierarchical multiple re-

gression analysis was applied. Findings indicate that 74.8% of the variance in word-of-mouth is accounted for by explanatory variables collectively, $F(6, 256) = 130.935$, $p < 0.001$. By inspecting individual contributions of the explanatory variables, the result shows that administrative quality ($B = 0.355$, $t = 5.325$, $p < 0.001$), technical quality ($B = 0.211$, $t = 3.094$, $p = 0.002$), interpersonal quality ($B = 0.233$, $t = 3.509$, $p = 0.001$), social resources ($B = 0.113$, $t = 2.799$, $p = 0.006$) significantly predict word-of-mouth. Thus, supporting hypotheses H_1: AQ $\rightarrow$ WOM, H_2: TQ $\rightarrow$ WOM, H_3: IQ $\rightarrow$ WOM and H_5: SR $\rightarrow$ WOM. Conversely, the results show that cultural resources ($B = 0.014$, $t = 0.251$, $p = 0.802$) and physical resources or self-efficacy ($B = 0.043$, $t = 1.041$, $p = 0.299$) do not significantly predict word-of-mouth, thus rejecting the hypotheses H_4: CR $\rightarrow$ WOM, and H_6: PR $\rightarrow$ WOM (see Tab. 1 and 2).

The purpose of this study was to provide empirical evidence about the role of organizational and customer operant resources in word-of-mouth generation. This study contributes to the rapidly growing body of literature on service-dominant logic, by emphasizing the importance of operant resources and organizational and customers' roles in word-of-mouth generation.

Among the three components of a customer's operant resources (i.e. cultural, social, and physical resources), social resources were found to significantly predict word-of-mouth supporting H_5: SR $\rightarrow$ WOM. When children are un-vaccinated or sick and need preventative healthcare against potential diseases, many of the parents due to the bearing of children and other day-to-day responsibilities of the family are not in habitual physical and mental state. Parents in these circumstances who own strong social support or social resources are capable of employing resources from others (family members, relatives, neighbors, friends, etc.) and are likely to benefit from these resources (Hau, 2019). These results are in line with Frempong et al. (2020), Hau (2019), Jetten et al. (2020), and Stickley et al. (2021), who underscored the significance of social resources in healthcare services and therefore, increased the prominence of relatives, neighbors, and friends associated with customers as the actors in the value-creation network (Vargo et al., 2023; Viglia et al., 2023). Therefore, the contribution of social resources of customers' abreast organizational operant resources during service provision conforms to the service-dominant logic hallmark that suggests multiple actors' contribution. Consequently, this study also affirms that the parents or caregivers, who are aware of the importance of childhood vaccination, are more likely to act as social resources when helping non-vaccinated children's parents by sharing their knowledge and experience about the vaccination and immunization of the children.

In contrast, the result shows that physical resources (or self-efficacy) have no significant impact on word-of-mouth rejecting H_6: PR $\rightarrow$ WOM. In preventative healthcare services for children, parents are relatively weaker in their physical and mental state of mind due to anxiety, worry about their child, sensitivity, and fear. Consequently, low physical and mental strength would often put limitations on the capabilities of parents to assemble and deploy their operant resources in the service process (Hau, 2019). These limitations also restrain the deploying of cultural resources or specialized knowledge of customers during service provision which disturbs the predictive capabilities of cultural resources towards word-of-mouth, therefore, rejecting H_4: CR $\rightarrow$ WOM.

Moreover, the role of the organization as an actor is also of critical importance in service-for-service exchange in value creation (Chandler and Vargo, 2011). In this study, the role of the organization was conceptualized through the contribution of operant resources according to the theory of service quality specifically administrative quality, technical quality, and interpersonal quality (Dagger et al., 2007). There was a significant relationship evident between these three operant resources and word-of-mouth thus supporting H_1: AQ $\rightarrow$ WOM, H_2: TQ $\rightarrow$ WOM, and H_3: IQ $\rightarrow$ WOM. These results corroborate the findings of other studies in the healthcare context (Dandis et al., 2022; Fattahi et al., 2022; Lu and Wu, 2016). The administrative quality which refers

Tab. 1: Final Regression with 95% confidence interval

	Unstandardized Coefficients		Standardized Coefficients			95% Confidence Interval for *B*	
Model	***B***	**Std. Error**	**Beta**	***T***	**Sig.**	**Lower Bound**	**Upper Bound**
Constant	0.461	0.138		3.353	0.001	0.190	0.732
Administrative Quality (AQ)	0.328	0.062	0.355	5.325	0.000	0.207	0.449
Technical Quality (TQ)	0.200	0.065	0.211	3.094	0.002	0.073	0.328
Interpersonal Quality (TQ)	0.222	0.063	0.233	3.509	0.001	0.098	0.347
Cultural Resource (CR)	0.015	0.059	0.014	0.251	0.802	−0.101	0.131
Social Resource (SR)	0.098	0.035	0.113	2.799	0.006	0.029	0.166
Physical Resource (PR)	0.046	0.044	0.043	1.041	0.299	−0.041	0.134

Note: Dependent variable is word-of-mouth.

Tab. 2: Summary of Findings

Hypothesis	**Regression Weights**	***B***	***t***	***p*-value**	**Hypothesis Supported**
H1	AQ → WOM	0.355	5.325	0.001	Yes
H2	TQ → WOM	0.211	3.094	< 0.001	Yes
H3	IQ → WOM	0.233	3.509	0.002	Yes
H4	CR → WOM	0.014	0.251	0.802	No
H5	SR → WOM	0.113	2.799	0.006	Yes
H6	PR → WOM	0.043	1.041	0.299	No
R^2	0.748466			< 0.001	
$F(6, 256)$	130.935				

Note: This table shows the summary of findings for the hypothesized relationship.

to relative ease and smoothness provided by the organization during the service process had a meaningful impact on word-of-mouth. The second impact on word-of-mouth is attributed to interpersonal quality. Interpersonal quality was measured by interactive aspects of healthcare staff with customers (parents). Consequently, the staff and employees of the organization play a crucial role in generating word-of-mouth, making employees another actor in the service system (Vargo et al., 2020). Equally important, the perceived expertise of the staff and employees, which was conceptualized by technical quality also significantly predicts word-of-mouth as per the findings of this study. Therefore service employee is a critical touch-point of service organizations facilitating preventative healthcare services. Aiding these propositions, the organizational resources need to be modified in a way that will create a positive perception of the experience during the encounter with the service provider.

In Pakistan, a common reason for non-vaccination or incomplete vaccination is a lack of parents' or caregivers' awareness about immunization (Hussain et al., 2021). This study addresses the problem of non-vaccination through word-of-mouth (Balraj and John, 1986) by investigating causative factors. Based on this study, these causative factors (operant resources) would predict the vaccinated child's parents or caregivers' intention to recommend the centers specific in their respective areas or counties, to their neighbors, relatives, and friends, by sharing their experiences and saying positive words. However, future studies can explore the relationship between positive word-of-mouth intention and an increase in actual participation or how word-of-mouth intention acts as an effective promotion medium for behavioral change in the childhood vaccination context. This is more desired to achieve long-term social marketing goals.

The vaccine is interpreted as an operand (rather operant) resource according to service-dominant theory. We argue that it is a crucial tangible product on which operant resources are applied (specialized skills and knowledge). However, mere vaccines availability in immunization strategy might not encourage promotion through word-of-mouth. Overall administrative setting of preventative healthcare should be designed to provide a more robust and smooth service flow in conjunction with the competence and interpersonal skills of the staff. This will integrate the organizational and customers' operant resources into more contextual value-creation activities, which is likely to increase positive word-of-mouth (Chandler and Vargo, 2011). Furthermore, it is understood that value-creation is not limited to an organization as the customer is value co-creator from a general perspective, which ultimately benefits the customer as a beneficiary (Vargo and Lusch, 2016). The study indicates empirical evidence for this proposition in childhood vaccination. The customer brings social resources such as assistance and support from relatives, family, and friends which are crucial before, during, and after childhood vaccination. This necessarily improves the service provision and leads to positive word-of-mouth.

6 CONCLUSION

The study contributes empirical insights to social marketing theory, particularly from a service-dominant logic perspective, and expands the literature on preventative healthcare services. By focusing on word-of-mouth behavior in the context of children's immunization services and elucidating operant resources in preventative healthcare services, it enhances understanding in these domains.

Employing hierarchical multiple regression analysis, the study underscores the significance of service quality dimensions in generating word-of-mouth, highlighting the pivotal role of customer-service provider interactions and interpersonal dynamics in preventative healthcare contexts. In addition, it underscores the personal nature of word-of-mouth generation in such services, providing valuable empirical evidence previously lacking in social marketing literature. Based on this study, we assert that in preventative healthcare campaign strategy, targeting parents for children immunization would not suffice the potential response and impact. The social marketers should target other actors represented in their campaigns as social resources influences consumers toward certain behavioral change. However, the question arises, what responsibilities fall on the service provider in the absence of social resources? We argue that an organization needs to have a holistic view and train their staff in a fashion that makes the staff act as a social resources, fulfilling the need to have a social circle before, during, and after service provision.

Our findings benefit social marketing researchers and scholars interested in this domain, as well as policymakers and social marketing organizations. We encourage future researchers to employ sampling techniques other than convenience sampling to remove generalization concerns, as well as conduct comparative studies of these factors on online vs. offline word-of-mouth behavior. Moreover, while internet penetration in Pakistan presents a valid limitation, alternative methods of data collection such as paper-based surveys can be considered for future research endeavors, as these methods could help ensure the inclusivity and representation of populations with limited internet access. While the study examines factors influencing word-of-mouth behavior, its impact on actual participation rates remain unexplored, indicating a critical area for future inquiry. Recognizing these avenues of future research is crucial for ensuring the robustness of findings in the field of social marketing and preventative health care services.

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8 ANNEX

Constructs	Items	
Administrative quality	AQ_1:	The administration system at the place where my child was brought for vaccination last time was excellent
	AQ_2:	The administration at the place where my child was brought for vaccination last time was of a high standard
	AQ_3:	I have confidence in the administration system at the place where my child was brought for vaccination last time
Technical quality	TQ_1:	The quality of the service I received at the place where my child was brought for vaccination last time was excellent
	TQ_2:	The service provided at the place where my child was brought for vaccination last time was of a high standard
	TQ_3:	I am impressed by the service provided at the place where my child was brought for vaccination last time
Interpersonal quality	IQ_1:	The interaction I had with the staff at the place where my child was brought for vaccination last time was of a high standard
	IQ_2:	The interaction I had with the staff at the place where my child was brought for vaccination last time was excellent
	IQ_3:	I feel good about the interaction I had with the staff at the place where my child was brought for vaccination last time
Physical resource/self-efficacy	PR_1:	I can always manage to solve my child's health problems if I try hard enough
	PR_2:	I can remain calm when my child is facing health difficulties because I can rely on my coping abilities
	PR_3:	When my child is confronted with a health problem, I can usually find a solution
Cultural resources	CR_1:	I knew well what I need to do during the vaccination at the place where my child was brought for vaccination last time
	CR_2:	I knew how to make the immunization and vaccination to be best benefits for my child
	CR_3:	I understood easily the instructions during the vaccination process at the place where my child was brought for vaccination last time
Social resources	SR_1:	I receive useful assistance from my relatives, friends, or people around me during my child vaccination process
	SR_2:	Relatives, colleagues, or friends share with me their knowledge/experience about vaccination or immunization of children
Word-of-mouth	WOM_1:	I share my experience with other people about the place where my child was brought for vaccination last time
	WOM_2:	When I have the chances, I will say positive things with others about the place where my child was brought for vaccination last time
	WOM_3:	I recommend the last place where my child was brought for a vaccination to others who seeks my advice

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STRATEGIC MEDIA MESSAGING OF STARTUPS AND ENTREPRENEURS BEFORE INITIAL PUBLIC OFFERING (IPO)

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ABSTRACT

This research delves into effective messaging strategies employed by companies to shape their reputation in anticipation of an initial public offering (IPO). Drawing insights from the analysis of 1162 media headlines encompassing 30 brands during their IPOs on NASDAQ or NYSE, the study offers valuable recommendations for entrepreneurs and startups engaging in rhetorical preparations for an IPO. By synthesizing the examination of successful companies' media framing with pertinent well-known communication frameworks (strategic communication and the PESO model), the article introduces the new 6I's model. This model serves as a comprehensive marketing guide, empowering entrepreneurs, and businesses to adeptly manage their company's reputation and highlight diverse accomplishments for the cultivation of a positive media image towards the IPO. The 6I's model encompasses messages centered on Increasing and rapid growth, Innovative technology, Immediate relevance, Individuals and personnel, In-charge management, and In-chronicle history and company tradition. Based on the suggested model, this study further develops the theoretical understanding of corporate narrative and strategic communication to mold the reputations of organizations.

KEY WORDS

tech organization, initial public offering, reputation, narrative, tech marketing

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1 INTRODUCTION

The initial public offering (IPO) event is a significant milestone for many organizations, as it represents wealth, recognition, and fame (Luo, 2008). The process of an IPO requires management and executives to concurrently navigate multiple interfaces, including economic factors such as investments, profits, and returns, as well as organizational changes in structure, workforce, and hierarchy, and the reputational impact on both the company and the IPO (Laskin, 2010). However, due to the media coverage surrounding IPOs, there has been a growing understanding of the representation of firm IPOs in recent years, with some studies examining media coverage post-IPO and others evaluating the impact of media coverage on firm stock prices retrospectively (Chen et al., 2020; Guldiken et al., 2017; Liu et al., 2011; Strauß and van der Meer, 2017). Despite this increased understanding, there remains a lack of knowledge on how companies manage their media presence during the IPO process and how they actively seek to enhance their reputation.

IPOs can be a pivotal moment in the trajectory of a startup (Li and Zhou, 2023), and effective media management, dialogue, and strategic communication are crucial, given the significant role that media plays in IPOs (Hallahan et al., 2007; Werder et al., 2018; Wiesenberg et al., 2020). Additionally, IPOs are a competitive organizational phase, making strategic communication an imperative aspect (Werder et al., 2018). Media-provided information can play a key role in shaping the perceptions and decisions of various stakeholders involved in the IPO process (Pollock et al., 2008; Pollock and Rindova, 2003). The current study aims to offer a toolkit of media messages for PR, entrepreneurs, and leadership to boost IPO success by summarizing media-provided information. It also contributes to discussions on strategic communication, start-up narratives, and organizational identity (Ala-Kortesmaa et al., 2022; Winkler and Etter, 2018).

While previous academic papers predominantly addressed the post-IPO phase, focusing primarily on financial and technical aspects of public offerings, our current study shifts its focus to the pre-IPO phase and concentrates on organizational communication aspects. Based on strategic frameworks from the literature and with an analysis of recent content, the study presents a fresh strategic tool for companies planning to go public, emphasizing the critical stage of media management for reputation management. As such, the paper begins with a theoretical background covering the marketing aspect of business and media framing theory. Subsequently, we delve into a strategic media management approach as a key element during the lead-up to an IPO. The following sections include the methodology chapter, the findings chapter introducing a novel model for messaging towards IPO, providing businesses with a practical tool for reputation management. This chapter is followed by a discussion and an outline for future research.

2 THEORETICAL BACKGROUND

2.1 The Marketing Path: From How to What

Rhetoric serves as a potent sociopolitical force (Ihlen and Heath, 2019). Organizational rhetoric refers to the strategic and purposeful way an entity communicates with various stakeholders at different stages. It is used to achieve different goals (Hoffman and Ford, 2010). In the tech field, PR practitioners shape and manage organizational rhetoric. As businesses grow, they go through different stages of development (Lewis and Churchill, 1983), and at each stage, the organization must communicate with stakeholders and try to persuade them to support the organization's cause, product, or service.

This process involves using multiple channels and communicating consistent messages across all channels.

PR practitioners, marketing, business, and management roles all play a part in the process (Mohr et al., 2014). They have a wide array of tactics to choose from to communicate with the stakeholders (Holm, 2006). Indeed, how, and where organizations should distribute content, and the importance of integrating tactical channels as a main strategy was extensively studied in the past two decades (Burnett and Moriarty, 1998; Engel et al., 1991). For example, the organization can use direct marketing tactic (Roberts and Berger, 1999; Stone and Jacobs, 1988; Walle, 1996), traditional advertising (Gretzel et al., 2000; Lal and Matutes, 1994; Wansink and Ray, 1996), public relations (Avraham, 2004; Wilcox and Cameron, 2006), social media promotion (Castronovo and Huang, 2012; Frey and Rudloff, 2010) or all combined.

Currently, we have a strong understanding of the methods and channels organizations use to communicate their stories, as well as the importance of consistent messaging across all promotional channels (Batra and Keller, 2016; Kitchen and Burgmann, 2010). However, there is less emphasis on the specific content of these messages, and how they may vary depending on the stage of the organization. This study aims to fill this gap by focusing on the message component of organizational communication. According to scholars, marketing messages are deemed important. Therefore, organizations adopt a coherent marketing message strategy (Leung et al., 2017). The concept of message strategy involves deciding on "what to say" within the realm of advertising or marketing communications (Taylor, 1999). Therefore, it is vital to pay empirical attention to the content and types of organization terminology (what to say). A rhetorical strategy may help stimulating an affective commitment to a particular cause (Willner, 1985). There may be a significant impact on narratives based on rhetorical features (Allison et al., 2013). It is challenging to comprehend rhetoric, messages and understand "what the organization wants to convey" without considering the framing idea.

2.2 Organizational Framing

The concept of framing involves the organization and packaging of information (messages) that is to be published (Simon, 2001). It has attracted significant attention in academic literature as a tool for evaluating the influence of media. Through an examination of the structure and construction of messages and content, one can gain insight into the motivations and actions of the sender (Gitlin, 1980; Goffman, 1974). Brands utilize framing to present their message in a manner that is most likely to be comprehended and received by their target audience. This involves emphasizing certain information and disregarding or suppressing other information to shape the audience's perception and comprehension of the message.

Hallahan (2000) argue that the creation of effective messages to reach strategic audiences is crucial. The narrative stands as a powerful communication method, and leveraging framing techniques empowers organizations to guide and portray their brand, products, and services in a positive and favorable manner (Prindle, 2011). For example, organizations may utilize framing to emphasize technological benefits if their target audience is particularly concerned with tech issues. Additionally, framing can be employed to make an organization appear more relatable and personal by highlighting the people behind the company, as well as its history and heritage, through various distribution channels. The use of framing concept allows organizations to present their message in a way that is most likely to be understood and accepted by their target audience, while emphasizing the most positive aspects of their brand, products, and services (Tsai, 2007). Now, it is essential to examine the factors that are involved in framing mechanisms.

2.2.1 Factors of Organizational Framing

Top management teams, in their daily operations, bear the responsibility of overseeing various domains such as technology, business, sociology, and organization. In small and emerging tech companies, it is customary for the founder-CEO to wear multiple hats, handling diverse roles and responsibilities (Davila et al., 2010).

The entrepreneur has the responsibility of overseeing the technical aspects of the technology, ensuring its efficiency and impact. On the business front, the entrepreneur takes charge of economics, finance, investments, company capital, and payments. In the socio-organizational aspect, the entrepreneur plays a pivotal role in shaping the work environment's climate and effectiveness, ensuring teams are synchronized, cohesive, and efficient (Otara, 2011). Nevertheless, the leadership and management are actively required to manage the internal communication process (Men et al., 2021), However, as we shall explore further, management plays a significant role in the external perception as well (Laskin, 2010, 2016), shaping narratives and building the organizational identity (Ala-Kortesmaa et al., 2022; Winkler and Etter, 2018).

Journalists frequently seek out input from business leaders when covering important business events and reporting on significant financial and technological advancements. Executives and entrepreneurs are responsible for managing media relations, representing their business to journalists, and sharing news about significant developments and the company as a whole (Werder et al., 2018). The leadership's role often includes giving interviews, sharing stories, and accurately representing the company.

Effective communication with stakeholders is crucial for the success of an organization. By collaborating closely with public relations experts (PR) as identified by Luttrell (2018), leadership can effectively convey a clear message and maintain a positive public image, thereby fostering trust among stakeholders (Saini and Plowman, 2007; Shan, 2019; Sloman, 2019; Tong, 2013). In particular, public relations practitioners and their technology clients often work to portray a positive image of the organization, particularly in anticipation of sensitive business events. Through the development, articulation, and shaping of a coherent narrative of entrepreneurship, PR practitioners and their clients work together to effectively communicate the organization's message during various defining moments of the startup, with a particular focus on the pivotal IPO phase.

2.3 Strategic Communication in the IPO Phase

Effective communication and promotion of an organization's message can be achieved through a strategic communication approach (Hallahan et al., 2007). While the field of strategic communication has seen significant theoretical development in recent years, there is a need for a deeper understanding of its application within organizations, particularly within the context of tech organizations, such as startups and global tech corporations, in various organizational phases (Werder et al., 2018). The topic of startup communications was the focus of a recent special issue (Godulla and Men, 2022), however, none of the articles addressed the specific communication challenges and considerations associated with the IPO stage, an area that this current study aims to address. Similar to other organizational phases, an IPO requires proper communication and marketing planning, strategy, and execution (Cook et al., 2006; Ma et al., 2017; Mumi et al., 2019). Therefore, management must adopt and implement a strategic communication approach (Holtzhausen and Zerfaß, 2015). As with any other corporate strategy, an IPO strategy should guide a company's communication strategy (Argenti et al., 2005).

Strategic communication, as defined by scholars, is the intentional utilization of communication by an organization to fulfill its mission (Hallahan et al., 2007). As emphasized previously, the IPO represents a crucial organizational mission that requires a well-defined strategic communication plan. This plan involves the coordination of actions, messages, images, and other forms of signaling or engagement, all intended to inform, influence, or persuade selected audiences (Paul, 2011). Typically, brands can share information with various stakeholders (Luttrell, 2018) through four main forms incorporated into the well-known PESO model (Dietrich, 2014), which

Tab. 1: The PESO model (fully controlled and semi-controlled media)

Type	**The PESO component**	**Refers to** (Macnamara et al., 2016, pp. 377–378)
Fully controlled media	Paid media	"Traditional advertising and other forms of content commercially contracted between organizations and mass media."
	Owned media	"Publications and digital sites established and controlled by organizations, such as corporate magazines, newsletters, reports and, more recently, organization Web sites, blogs, and official Facebook pages."
Semi-controlled media	Earned media	"Editorial publicity that is generated by organizations through media releases, interviews."
	Shared media	"Popular social media such as Facebook, Twitter, YouTube, Tumblr, Instagram, and Pinterest, national networks such Sina Weibo in China, as well as blogs that allow comments to be posted."

comprises four components representing both traditional and new forms of media distribution (Macnamara et al., 2016; see Tab. 1).

The Paid and Owned components of the PESO model are fully-controlled platforms that can be managed by the organization and the marketing team. In these components, the organization is responsible for all aspects of the production and supply chain, and can control the content that is published and when it is published (Men and Tsai, 2016; Yue et al., 2019). These channels can provide stakeholders with information about the company and its agenda, but they may be perceived as less credible by some individuals, as the target audience may understand that the channel is operated based on the interests of the brand.

Furthermore, the Earned and Shared components of communication are semi-controlled platforms, in which organizations possess limited authority over the messages that are disseminated through these channels. As a result of the divergent motivations of the parties involved, interactions between top-management team members and journalists may yield either positive or negative media coverage. Nevertheless, it is generally acknowledged that content that is disseminated through the business press is considered trustworthy and reliable. Consequently, companies often utilize traditional media platforms, such as print newspapers and news websites, as a means of conveying messages and establishing credibility prior to an IPO (Laskin, 2017). It is important to note, however, that regardless of whether a company chooses to utilize fully controlled or semi-controlled communication channels, the organization and its top-management must be cognizant of the potential rhetorical implications of their actions.

2.4 Entrepreneurship Rhetoric and Organizational Messages

The selection of an appropriate distribution channel for startups is of utmost importance (Wiesenberg et al., 2020). Marketing practitioners and members of the top management team (TMT) must grasp the evolving methods through which the public communicates, connects, consumes, and shares information (Burcher, 2012). However, as a part of the strategic communication process, startups not only choose the right channels of communication but also determine the suitable rhetoric and messages (Wiesenberg et al., 2020). There are three distinct paths of rhetorical research: "rhetoric and identity; rhetoric, culture, and community; and rhetoric and persuasion" (Spinuzzi, 2017).

Every IPO process involves some level of persuasive effort aimed at stakeholders such as investors, partners, employees, and the public (Li and Zhou, 2023). Organizations consistently employ rhetorical strategies by narrating stories that spotlight their accomplishments, successful individuals, and key events. In crafting an effective strategic communication plan, startup

management must precisely define the "core messages" (Wiesenberg et al., 2020).

Turning to the empirical aspect, the study draws upon examination by Allison et al. (2013) of the connection between rhetoric and entrepreneurship and the necessity to emphasize positive aspects, expansions, successes, and achievements in order to guide a brand's core rhetorical strategy towards an IPO. Through examining those who have already undergone IPO and analyzing how media topics have been presented over time, we may obtain a more comprehensive comprehension of the types of narratives that tech companies will construct. As a result, we pose the following research questions:

- RQ_1: *What are the key accomplishments and framing strategies that are highlighted in media appearances of companies during the period leading up to an IPO?*
- RQ_2: *What framing can tech companies take to shape reputation and increase the likelihood of a successful IPO?*

By answering these questions, we can create a list of strategic messages that PR practitioners, leaders, and management can use in future IPO preparations.

3 METHOD

Our research involved analyzing a sample of 30 tech companies that went public on the NYSE or NASDAQ in 2021 (Kunthara, 2021). These companies, which are listed in Tab. 4 in the Annex, are located around the world and represent various industries, with a wide range of products and services.

3.1 The Database

The OECD report suggests that Crunchbase is a trustworthy and comprehensive source of information concerning startup and technology company activities and financing across various countries (Dalle et al., 2017). The Crunchbase archive has increasingly been utilized in social science and economic research as it contains a wealth of information on tech companies, individual entrepreneurs, financial data, business transactions, and media coverage (Ferrati and Muffatto, 2021; Liang and Yuan, 2016; Żbikowski and Antosiuk, 2021). The current research utilized systematic data extraction methods to employ the Crunchbase archive as a primary source of data.

Scholars have suggested that a collection of headlines allows for quantitative analysis. For example, conducting a longitudinal study on the frequency of headlines related to a specific issue can reveal the evolution of the prominence given to that topic over time (Develotte and Rechniewski, 2001). In consonance with this framework for the discourse analysis of newspaper headlines, this current study also employed media coverage titles prior to IPO as its research unit. To this end, each company's Crunchbase profile was consulted, which included the headlines published by the media pertaining to the respective company. The Crunchbase database comprised 11,624 headlines across all 30 brands from 2011 to 2020. To reduce the amount of content, a cluster sampling strategy was employed, with each brand serving as an individual cluster. Out of the total number of headlines for each brand, a random sample of 10% was selected (Tab. 2). Each headline was given a unique ID (number). I manually selected a random 10% of the content from the total headlines for each brand by utilizing the `https://www.random.org/` software to determine the ID on each occasion. The collected headlines from each brand were then compiled into a unified database. Thus, the study took into consideration the relative size of each brand. A total of 1162 headlines were analyzed, with the entire title serving as the unit of analysis ($N = 1162$).

It is imperative to emphasize the significance of an extended period of media coverage for our case. Within the context of an IPO, companies undertake thorough preparation and planning over a prolonged duration. Simultaneously, the

continuous activities and organizational advancements throughout the company's lifecycle carry implications for its trajectory. This principle extends to the media-marketing domain, where headlines and articles published during a company's early stages significantly shape its image. This influence extends to shaping both the overall positioning of the company and the success of the IPO. Essentially, media discourse and headlines constitute integral components of strategic considerations, aligning with financial and legal aspects. Therefore, the analysis of media headlines from 2011 to 2020 is chosen to comprehensively understand the dynamics leading up to the IPO in 2021.

3.2 The Analysis

In this study, a thorough analysis of media headlines was conducted to identify the most common and significant themes. The methodology employed was primarily informed by Braun and Clarke's (2006) framework for thematic analysis. In thematic analysis, a systematic protocol contributes to the credibility and trustworthiness of the identified themes, ensuring that they accurately represent the underlying patterns within the qualitative data.

Indeed, to ensure reliability, human reading and analysis were repeated until the media material was exhausted through the following steps:

1. Sequential rereading of each media headline.
2. Identification of overarching themes. This step combines both human reading and the automated Voyant Tools software, which is suitable for analyzing a variety of digital texts (Welsh, 2014). It is particularly useful for researchers to reveal term frequency and connections (Gregory et al., 2022). In this instance, the titles obtained from Crunchbase were systematically uploaded to `www.voyant-tools.org` for mapping of headlines, identification of key terms within media headlines, and cross-brand comparison of recurring terms (Edwards-Schachter and Wallace, 2017; Hetenyi et al., 2019). This process aimed to provide a broad understanding of the conceptual framework of the corpus and to generate an organized illustration of the interrelation of the key terms (see Fig. 2 in the Annex).
3. Refinement of key concepts into more specific themes.
4. Characterization and categorization into six predominant types.

Thus, by relying on previous theoretical frameworks for strategic communication messaging (Hazleton, 1992, 1993; Werder, 2014), the results chapter proposed a new messaging model for brands towards an IPO stage.

Tab. 2: Companies and Media titles frequency (Crunchbase, 2024)

	Company	Total titles	Media titles (10%)
1	Didi Chuxing	2766	277
2	Coursera	1628	163
3	Duolingo	724	72
4	Outbrain	696	70
5	Qualtrics	576	58
6	DigitalOcean	494	49
7	Sprinklr	415	42
8	Kaltura	392	39
9	SentinelOne	386	39
10	Couchbase	372	37
11	Poshmark	350	35
12	Bumble	349	35
13	Affirm	310	31
14	DoubleVerify	263	26
15	AppLovin	237	24
16	Compass	193	19
17	Coupang	177	18
18	Braze	176	18
19	Allbirds	174	17
20	GitLab	164	16
21	Nubank	131	13
22	Playtika	121	12
23	Remitly	114	11
24	WalkMe	112	11
25	Confluent	67	7
26	Riskified	66	7
27	Blend	55	6
28	Monday.com	53	5
29	Clear	37	4
30	DISCO	26	3
Total		11624	1162

4 RESULTS

Organizations lean on storytelling techniques to disseminate their accomplishments and positive messages in media leading up to an IPO (Allison et al., 2013; Edwards et al., 2002; Robinson and Blenker, 2014). In line with Gabriel (2000, 2004), the current study show that organizations implement stories and potential media narratives in their texts. As a result of the analysis process, our study identified six types of narrative that startups can utilize prior to an IPO. These messages were consolidated into a new strategic model, referred to as the 6I's messaging approach, which emphasizes the positive aspects of the startup and highlights the company's achievements. This type of entrepreneurial rhetoric and information presents the brand as strong, easily understandable, and persuasive to various stakeholders (Wiesenberg et al., 2020). The current chapter elaborates on this new model based on a prior theoretical framework for strategic communication messaging (Hazleton, 1992, 1993; Werder, 2014), see Tab. 3.

4.1 The 6I's Messaging Model

Academic literature has established that media stakeholders' information dissemination can impact the valuation and pricing of the company leading up to the IPO (Amaya et al., 2022; Cheung et al., 2020; Gupta et al., 2022; Loughran and Ritter, 2004). The IPO procedure, in which a private company transitions to public ownership, can prove to be a challenging experience for start-ups due to its complexity and requirement of disclosing previously private information. Hence, top management and public relations (PR) personnel strive to establish effective communication and maintain a favorable reputation prior to the IPO stage through strategic messaging (Bourne, 2016; Shan, 2019; Sloman, 2019) to ensure the desired results (Saini and Plowman, 2007; Tong, 2013; Wiesenberg et al., 2020).

According to Laskin (2017) trust is a central aspect of strategic communication activities, and the establishment of this trust with various stakeholders is vital. PR professionals and tech industry leaders have significant communication decisions to make in preparation for an IPO. These decisions are aimed at shaping the perceptions of current and potential investors regarding the organization's performance and future prospects through strategic communication choices (Hemmings et al., 2017, p. 48). As detailed in subsequent sections in our study, PR practitioners, leaders, and marketing representatives can communicate and disseminate six types of financial and non-financial information (Laskin, 2010, 2016), see Fig. 1. The findings chapter employs theory-driven analysis with the goal of establishing a connection between the newly discovered insights and pre-existing theoretical knowledge. The six new messaging types presented in Fig. 1 are tied and connected to prior strategic approaches (Werder, 2014; Hazleton, 1992, 1993) and the well-known PESO model (Dietrich, 2014). Together, they serve as a holistic model for tech companies to adopt to maintain a good reputation.

4.1.1 Increasing and Rapid Growth

The Informative Strategy revolves around delivering objective facts, under the premise of engaging a rational and motivated audience (Werder, 2014). During the lengthy process of an IPO, public relations practitioners and management may disseminate information regarding the substantial growth of the company and emphasize its expanding size and strength. Growth and territorial expansion are regarded as key markers of a robust business (Hogarth-Scott et al., 1996).

According to our analysis, the management of the high-tech company, therefore, seeks to publicly showcase the company's progression towards an IPO by demonstrating its growth. This media representation is based on the notion that the company has undergone rapid growth, as evidenced by its financial performance (Barringer et al., 2005; Zhang et al., 2008). As a result, the brand makes every public appearance an opportunity to communicate a positive message of growth through various

Tab. 3: The 6I's messaging strategy: summary of tech organizational narratives

The strategy (Hazleton, 1992, 1993; Werder, 2014)	**The message 6I's**	**Intended to**	**Terms from the media headlines**
Informative Strategy	Increasing and rapid growth	Demonstrating the company's growth, such as through economic growth, employment, or expansion of branches, can help to show the company is thriving and has a positive trajectory. This is important to show the company's value and potential to stakeholders.	raises, funding, expanding, investor, round, increase
Facilitative Strategies	Innovative technology: the next generation	Highlighting the company's technological superiority and its importance to society can help to demonstrate the value of the company's products and services. This component helps to explain why the company's offerings are worth the investment.	service, innovation, tech, produce, launch
Co-Operative Problem-Solving Strategy	Immediate and relevant	Staying relevant by addressing current issues on the public agenda can help to increase the perceived legitimacy and value of the company and its products among consumers. This component helps to keep the company and its products relevant and top-of-mind for the target audience.	solution, serve, help, valued, provide
Bargaining Strategy	Individuals and persons	Emphasizing individuals within an organization can help to humanize the brand. This component shifts the discourse from a technical and functional discussion about technology to one that focuses on people and the factors that drive development. It makes the brand more relatable and personal.	team, people, employees
Power Strategy	In-charge quality management	Bringing attention to the company's executives and policymakers can help to establish their credibility and validate their decision to go public. This component helps to showcase their leadership abilities and emphasizes the company's potential for success.	executives, leadership, CEO, founder, co-founder, VP, manager
Persuasive Strategy	In-chronicle history and company tradition	Describing the organization's history can help to highlight its continuity and long-term vision. This component emphasizes the company's heritage and its potential for a bright future. It helps to show the company has a solid foundation and a clear direction for growth.	established, founded, early days

means (Armstrong et al., 2014). For example: "Kaltura acquires Rapt Media", "Outbrain buys Ligatus to expand in Europe", "Riskified raises 25M$ in growth round", "Playtika opens London studio".

This aspect involves leveraging compelling statistics. Companies frequently announce their capital fundraising rounds, expansion into new markets, establishment of new offices, and creation of job opportunities. As part of their ongoing growth strategy, they underscore their significant recruitment efforts. Moreover, the growth narrative utilizes namedropping, with some organizations mentioning renowned brands and celebrities in their marketing campaigns. Namedropping holds considerable marketing value, as it is often overlooked despite being regarded as a crucial element in high-tech industry marketing (Davies and Brush, 1997). The act of namedropping occurs when the brand (advertiser) seeks to associate itself with a higher class by referencing the name

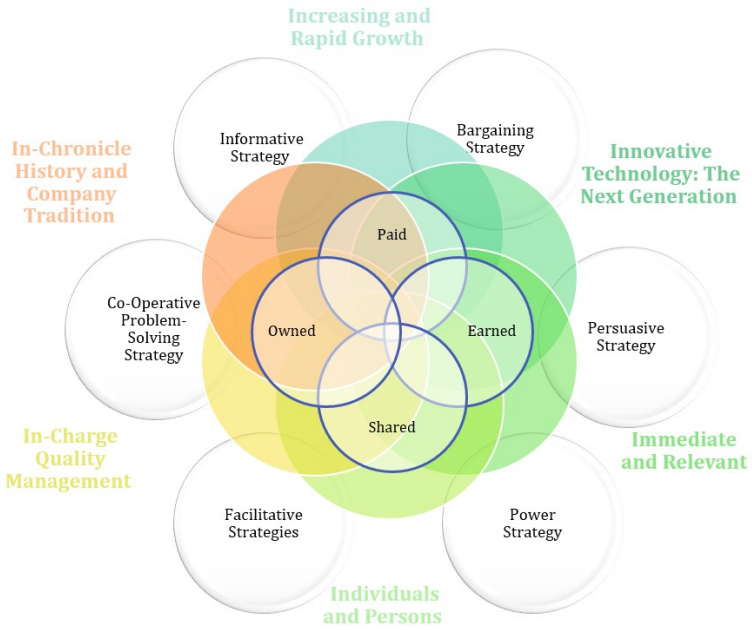

Fig. 1: The 6I's messaging model

of another well-known entity. For example: "Google and Coursera launch program to train more IT support specialists". Prior to an IPO, private, less known brands tend to use the names of well-established brands to enhance their image and credibility. By mentioning the names of well-regarded entities (that hold a positive image), startups that are pursuing an IPO position themselves as credible and authoritative.

4.1.2 Innovative Technology: The Next Generation

The utilization of a facilitative strategy by organizations serves to make their resources readily available to the public (Werder, 2014). In the realm of technology, a company's primary products and services is a resource, which can also act as a catalyst for promoting towards an IPO. Many high-technology companies originate from a single promising idea (Gupta et al., 1985). Ahead of an IPO, technology-based brands tend to disseminate communicative messages that highlight their key technology (Mohr et al., 2014). Such communications usually contain information about newly introduced features or improvements to existing company products (Mashiah, 2021, 2022). In other words, our study indicates that companies should focus on publishing content related to technology and innovation. For example: "Qualtrics Launches Innovative Customer Experience Enhancements", "Remitly partners Onfido to onboard customers using AI-based technology", "One to use its AI-powered technology to protect AASA against cyber-attacks". In the high-tech sphere, which is primarily product-driven, a key determinant of commercial success is the technological superiority of the product (Davies and Brush, 1997). In the lead up to an IPO, entities often rely on their existing technology instead of introducing a new, unfamiliar product, as a means of demonstrating stability and confidence and emphasizing their core expertise (Davies and Brush, 1997; Viardot, 2004). Before IPO these media texts that promote technological ideas generate a sense of stability and confidence among the company's stakeholders, thereby enhancing the company's position (Mohr et al., 2014). As we can see in the following examples: "These Innovative Startups Take Education to the Next Level", "4 breakthrough companies

driving innovation in the cloud". Indeed, today, many brands strategically adopt tech rhetoric to be portrayed as innovative and cutting-edge (Mashiah, 2024a, 2024b). Current analysis indicates that adopting this type of rhetoric can also be particularly effective before an IPO, as startups grow and expand.

4.1.3 Immediate and Relevant

The Co-Operative Problem-Solving Strategy entails an open exchange of information to establish a common understanding of the problem and mutual goals. This approach leads to the sharing of perspectives and responsibilities regarding the issue (Werder, 2014). According to our analysis, as a tech company approaches its IPO, one of the ways to maintain a prominent media presence is to publish content that emphasizes the relevance of the company to its target audience. Any brand that communicates with its target audience before IPO, usually draws the attention to routine things, communicates stories with low processing intensity (Carston, 2013; Sperber and Wilson, 1986). This helps to increase the tech company's relevancy and strengthen its public position.

For example, a tech brand on the path to an IPO may publish content that emphasizes customer satisfaction, such as testimonials and recommendations, as well as highlighting stories of satisfied customers and new contracts. This conveys a sense of public demand and need for the technology, positioning it as an essential service on the market. As we can see here: "AppLovin launches MAX In-App Bidding Monetization Solution and achieves impactful results". In addition, the brand rides on current issues, events and public lapse, by convinces consumers that the technology he holds can be the solution any problems. Interesting examples were published during the Covid-19 pandemic showcasing a relevant technological solution for social interactions, such as "Bumble launches new features to help you date during quarantine" and the trend of dating apps bucking the downward ad spend trend despite the pandemic.

4.1.4 Individuals and People

Throughout history, one of the foremost motivations for companies has been to achieve profitability. Over the years, companies have cultivated a significant infrastructure of organized invention and innovation, with the firm belief that it will result in profitable new ventures (Levitt, 1960). Indeed, for this reason, technology organizations pay close attention to their customers and comprehend their technological needs (Moriarty and Kosnik, 1989). To become profitable, tech companies push messages about their products with the intention of selling more.

Nonetheless, technology cannot sustain itself in isolation, thus, in addition to showcasing the profound innovative nature of the company, the brand also highlights the individuals responsible for creating this technological marvel (Bowers et al., 2006). As a component of the Bargaining Strategy, organizations use contrasting symbols that differentiate between groups, such as "we", and "they" (Werder, 2014). Our analysis revealed that the narrative of "teamwork" is a crucial aspect of the brand's message communicated to the public, especially in the context of an IPO. For instance: "Inside GitLab, the startup with the largest all-remote team in the world".

Technology is constructed by individuals who play a pivotal role in driving technological development and progress (Liu et al., 2015). Hence, the brand's messaging may center around the actions of its individuals and their contributions to the success and growth of the business. The brand's leadership, inclusive of its CEO and founder, aims to convey a spirit of collective effort and teamwork, emphasizing its crucial role in enabling the IPO. By highlighting the competence of the personnel responsible for the technology, the company underscores the importance of professionalism, collegiality, and teamwork. This strong message finds expression in the media through the acknowledgment bestowed by top management upon the teams. Clearly, a robust organizational culture like this presents the organization in a favorable light.

4.1.5 In-Charge Quality Management

The Power strategy, as propounded by Werder (2014), involves the utilization of positive coercion, where the source of the message holds control over an outcome that is desired by the recipient of the message. This strategy is often seen during IPOs, when a company experiences significant growth and an increase in its workforce, potentially dispersed globally. The aspect of people, specifically those in management positions, also holds a critical role in the strategic messaging of an organization. As the controlling administrators, managers are viewed as the most accountable figures and are expected to have a grasp of marketing and branding (Ward et al., 1999). These managers may either be responsible for the messaging or be a part of the messaging narrative.

We reveal in our study that the senior leadership of the brand, such as the CEO, VP, and department heads, is crucial to the success of the organization, and their information is deemed necessary for IPO processes. The leadership is highlighted as a valuable media asset through diverse channels, including in-depth interviews and brief commentary on newsworthy topics. This emphasis aims to underscore their skills, competencies, decision-making abilities, professional successes, and track record of accomplishments. Ultimately, this strategic approach contributes to ensuring the stability of the company (Swiercz and Lydon, 2002). Here are few examples: "Meet the CEO who once turned down a $500 million offer for his startup", "Kaltura's CEO tells us where the future of online video is headed", "Poshmark CEO: great mobile design is simplicity", "Qualtrics CEO Ryan Smith [...] taking his company global", "Bumble's founder is on a mission to clean up the internet", "Scaling to $100 million ARR: 3 founders share their insights", "20 executives tell what they do every day to succeed".

4.1.6 In-Chronicle History and Company Tradition

The Persuasive Strategy involves selectively presenting information (Werder, 2014). Another category of information is historical, where the organizational narrative plays a crucial role in conveying its tradition and history. Research, encompassing both theoretical and practical aspects, into the history of businesses and organizations has consistently been a subject of enduring interest (Godfrey et al., 2016; Kipping and Üsdiken, 2014; Rowlinson et al., 2014). As such, we found that a promotional plan ought to encompass a thorough representation and messaging of the birth and inception of the organization, as well as its starting point. Upon considering the people and technology involved, it becomes imperative to delve into the historical narrative with greater scrutiny. According to Kirkwood (2019) "history relates to the seeking of details regarding the past, heritage is the story we tell about ourselves in a way that gives meaning to our existence over time, explains the way we are now, and guides for the future" (p. 298).

The historical aspect continues to hold prominence among brands, as demonstrated by the analysis "When Duolingo was young: the early years". Indeed, history is fundamentally a narrative (Homer, 2006). Typically, a company undergoes an IPO after several years of operation, marking a significant milestone in its history. The IPO presents an opportunity for the company to showcase its rich history and highlight its record of accomplishments. A narrative story unfolds, chronicling the company's journey from its inception to the IPO, encompassing its growth, challenges, and triumphs along the way. This narrative serves as a historical record, affirming that the company has deep roots and is steadfast in its commitment. Often featured in the media, a media outline provides insights into the "first and early days" of each brand under consideration.

5 DISCUSSION AND CONCLUSION

The IPO represents a crucial turning point for start-ups and businesses, both from a financial and reputation standpoint. While prior academic papers dealt with the outcome of media coverage (Chen et al., 2020; Guldiken et al., 2017; Liu et al., 2011; Strauß and van der Meer, 2017), our study shift to the strategic media management domain. Hence, the things business needs to say to gain a positive media coverage towards the IPO stage. Before an IPO, public relations practitioners are obligated to establish a robust media presence for the client, by publishing narratives that reinforce the positive image of the organization. To establish the organization's worthiness for investment, it is imperative to emphasize its achievements through a range of messages that showcase its growth, technological advancements, the individuals responsible for product development, the leadership and management team, its history, and current relevance.

The IPO stands out as a widely discussed organizational event that attracts considerable research attention. What sets the present study apart from prior research is its innovative perspective. While most studies have focused on the direct media aspect, specifically the discourse following the IPO, this research explores the operational dimensions that can heighten the significance of the IPO event. The study provides valuable tips for companies planning future issuances, representing a paradigm shift. The present study introduces a variety of messages, offering insights applicable to any business anticipating an IPO.

Certainly, businesses and startups need to effectively handle communication, and at times, they may require well-defined models for this purpose (Godulla and Men, 2022). Previous studies suggest that a successful IPO necessitates effective communication and marketing planning, strategy, and execution (Cook et al., 2006; Ma et al., 2017; Mumi et al., 2019). Indeed, according to our research, there are six primary messages that traverse various aspects of the organization and can be integrated into other phases while maintaining significant significance in the IPO stage. These messages should concentrate on the accomplishments of the organization across diverse contexts and be formulated in a simple manner to supplement other marketing efforts. They can be incorporated into all PESO media components (Macnamara et al., 2016).

It is imperative to note that once an organization goes public, its internal data becomes publicly accessible and must be voluntarily disclosed through sources such as the IPO prospectus. Visibility is a key factor in this process. Our research suggests that the organization should publish a variety of media and public messages, in contrast to the period of relative silence that precedes an IPO. During this time, the organization concentrates on handling formalities "behind the scenes" and the IPO process may involve a period of reduced activity. Eventually, this quietude terminates and the organization becomes more exposed.

After analyzing the messages and their substance, it is appropriate to investigate the sources that enable the dissemination of these messages. Communication is a dynamic process that may involve changes such as hiring or termination of employees, reflecting the evolving nature of organizations. Hence, it is crucial that the messages are conveyed by a credible source within the company, and this should not be restricted to top management alone. In fact, today, all employees and members of the organization can be part of this process, yet the source should embody a strong alignment with the organization's values (Zerfaß et al., 2018). Hence, it's essential to recognize the IPO phase as a multifaceted and multilayered process. Treating the IPO as an isolated event, separate from other stages of organizational development, and if organizations pursue it solely for opportunistic motives would be mistaken. The IPO typically emerges because of the organization's achievements and its capacity to overcome diverse challenges. As a result, the IPO can serve as a symbol of prestige, showcasing the organization's triumph and po-

sitioning it as a vital element in the company's communicative arsenal, delivering the message "we have successfully achieved the momentous accomplishment of an IPO".

6 LIMITATIONS AND FUTURE RESEARCH

This research critically examines multiple narrative frameworks and contends that public relations professionals catering to high-tech clients can gain insights by analyzing how the media portrays the success of IPOs. The study proposes a practical tool for public relations practitioners working with startups to assist them in preparing for IPOs. However, it is important to acknowledge the limitations of the study, recognizing that headline analysis and organizational rhetoric mapping may have constraints due to the diverse framing techniques employed by journalists and editors during the production process. Nevertheless, considering the ultimate goal of a company to generate favorable publicity, attention-grabbing headlines about IPOs can serve as a valuable starting point for analysis.

The issue of sampling must also be considered. The size of the sample was relatively small, consisting of only thirty tech companies that went public within a single year. However, the study relies on a certain level of historical data. As explained in the methodology chapter, the content analyzed in this study covers a significant period of time, spanning a decade prior to the IPO. This method allows for the examination of the brand's general messages over time prior to the IPO process. It is important to note the absence of a comparative perspective. Instead of focusing on the distinct voices of individual brands, the aim was to identify shared themes and rhetorical connections among tech brands. Future research could conduct a more comprehensive analysis by comparing companies from diverse industries that have undergone IPOs at different points in time and exploring the rhetorical distinctions between each brand. This would enable a deeper understanding of how brands from various fields communicate their messages.

It is crucial to acknowledge an additional limitation of this study, which may also be considered a strength in some aspects. The six key rhetorical themes identified through an extensive content analysis of media-mediated appearances do not consider the actual conduct and intentions of Public Relations (PR) practitioners. Although the rhetoric of accomplishment demonstrates a considerable degree of accuracy, its validation could be further enhanced through future research that involves direct engagement with stakeholders and leaders within the brand. This would provide valuable insights into the particular messages that the organization seeks to convey through the media in the lead-up to the IPO. Additionally, future research could explore the practical contexts in which these messages are integrated into the media, as well as the interplay between management, PR, and spokespersons in developing messaging strategies.

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8 ANNEX

Tab. 4: List of firms went public (Crunchbase, 2024)

	Company	Homepage	Industries	IPO Date (First day of trading)	IPO Price ($)	IPO Valuation (billion $)
1	Poshmark	www.poshmark.com	E-Commerce, Fashion, Marketplace, P2P	14.01.2021	42	3.00
2	Playtika	www.playtika.com	Digital Entertainment, Gaming, Mobile apps	15.01.2021	27	11.00
3	Qualtrics	www.qualtrics.com	Consumer, Market research, SaaS, Software	28.01.2021	30	15.00
4	Bumble	www.bumble.com	Apps, Consumer, Dating, Social network	11.02.2021	43	8.20
5	Coupang	www.coupang.com	Consumer service, E-Commerce, Internet, Retail	11.03.2021	35	60.00
6	DigitalOcean	www.digitalocean.com	Cloud Computing, SaaS, Web hosting,	23.03.2021	47	5.00
7	Coursera	www.coursera.org	E-learning, EdTech, Education, Internet	31.03.2021	33	4.30
8	Compass	www.compass.com	Real estate, Property management	01.04.2021	18	8.00
9	AppLovin	www.applovin.com	Advertising, Developer tools, Mobile, Apps	15.04.2021	80	28.60
10	DoubleVerify	www.doubleverify.com	Advertising, Analytics, Brand marketing, Digital marketing, Software	21.04.2021	27	4.20
11	Monday.com	www.monday.com	SaaS, Task management, Project Management	10.06.2021	155	7.50
12	WalkMe	www.walkme.com	E-learning, Software, Product Management	16.06.2021	31	2.50
13	Sprinklr	www.sprinklr.com	Social media, enterprise software, advertising platforms, digital marketing	22.06.2021	15	3.70
14	Confluent	www.confluent.io	Enterprise software, cloud data service, analytics,	24.06.2021	36	9.10
15	SentinelOne	www.sentinelone.com	Cyber security, artificial intelligence, network security	30.06.2021	35	10.00
16	Didi Chuxing	www.didiglobal.com	Mobile apps, ride sharing, transportation	30.06.2021	14	73.00
17	Clear	www.clearme.com	Biometrics, security, facial recognition	29.06.2021	31	4.50
18	Blend	www.blend.com	FinTech, software, financial services	16.07.2021	18	4.00
19	Kaltura	corp.kaltura.com	SaaS, developer APIs, video streaming, video on demand	21.07.2021	10	1.24
20	DISCO	www.csdisco.com	Legal tech, IT, artificial intelligence	21.07.2021	32	2.50
21	Couchbase	www.couchbase.com	Big data, database, enterprise software, cloud data services	21.07.2021	24	1.40
22	Outbrain	www.outbrain.com	Advertising, Internet, digital marketing, content discovery	23.07.2021	20	1.10
23	Duolingo	www.duolingo.com	E-learning, education, mobile apps	28.07.2021	102	3.70
24	Riskified	www.riskified.com	E-commerce, fraud detection, risk management, machine learning	28.07.2021	21	3.30
25	Remitly	www.remitly.com	FinTech, payment, financial services	23.09.2021	43	6.90
26	Affirm	www.affirm.com	FinTech, payment, financial services	13.10.2021	49	11.90
27	GitLab	about.gitlab.com	SaaS, software, open source, cloud security, developer tools	14.10.2021	77	11.00
28	Allbirds	www.allbirds.com	E-commerce, fashion, manufacturing, shoes	03.11.2021	15	2.20
29	Braze	www.braze.com	Software, CRM, analytics, marketing	17.11.2021	65	6.00
30	Nubank	www.nubank.com.br	FinTech, financial services, credit cards. Banking	09.12.2021	9	41.00

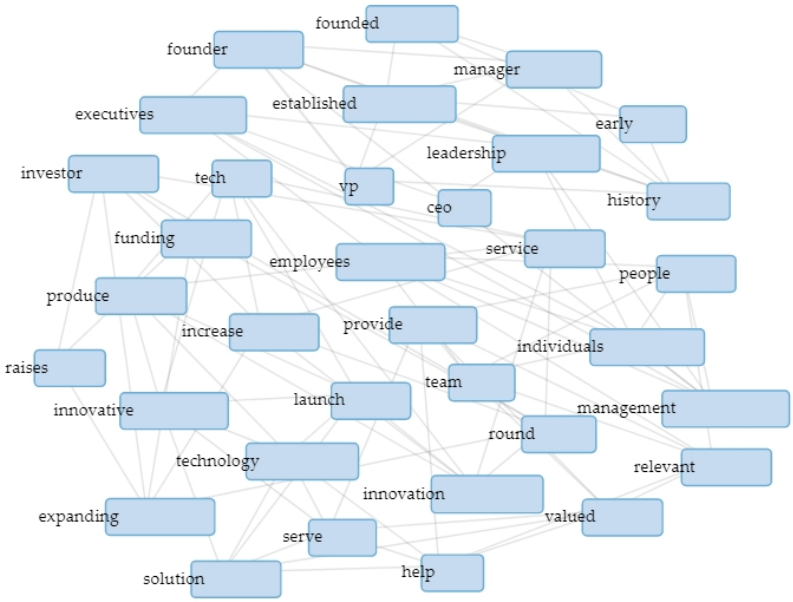

Fig. 2: Interrelation of the key terms (By Voyant tools)

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IMPROVING IOT MANAGEMENT WITH BLOCKCHAIN: SMART HOME ACCESS CONTROL

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ABSTRACT

Smart IoT devices, such as lights, locks, washing machines, security cameras, etc., are becoming omnipresent in households and companies across all industries. However, most of these devices communicate over non-secure local protocols or via cloud services where security policies are not transparent. Vulnerabilities may lead to unauthorized access to such IoT devices. Blockchain is a technology that brings security by design and can be exploited also in the area of controlling access to IoT devices. The goal of the paper is to test the use of blockchain with IoT devices to increase the security of device usage while ensuring that the user experience remains efficient and user-friendly. Three approaches to use blockchain are proposed and tested: a) application without the blockchain using standard HTTPS protocol; b) an application using blockchain, where users sign the transactions themselves; c) an application using blockchain where the server signs the transactions. The paper successfully shows that blockchain can be used to enhance IoT device security, with an focus on user-friendliness testing to ensure the solutions are practical for everyday use.

KEY WORDS

blockchain, IoT, access control, smart home, Ethereum, Bloxberg, Solidity, smart contracts

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1 INTRODUCTION

In recent years, the Internet of Things (IoT) has emerged as a transformative technology, integrating the physical world with digital systems to enhance efficiency, data collection, and automation. This integration has proliferated in various sectors, including healthcare, agriculture, and smart homes, yielding significant benefits. However, with the expansion of IoT applications, the need for robust security mechanisms has become paramount, especially

GONO, Andrej, PISAŘOVIC, Ivo, ZEJDA, Martin, LANDA, Jaromír, and PROCHÁZKA, David. 2024. Improving IoT Management with Blockchain: Smart Home Access Control. *European Journal of Business Science and Technology,* 10 (2): 225–241. ISSN 2694-7161, DOI 10.11118/ejobsat.2024.012.

considering the sensitivity and volume of data involved (HaddadPajouh et al., 2021).

The introduction of blockchain technology presents a promising solution to these security challenges (Dorri et al., 2017). Blockchain, a decentralized and distributed ledger technology, is renowned for its robust security features, transparency, and immutability. By integrating blockchain with IoT, a secure, transparent, and efficient framework for managing IoT devices and the data they generate can be created. This integration not only enhances security but also fosters trust among users and stakeholders involved in IoT ecosystems (Hosseini et al., 2023).

This article aims to explore the potential of blockchain technology in providing secure access to IoT devices and to provide a methodology on how to use blockchain for the purpose of managing access to IoT devices. Many theoretical principles have been devised for these purposes, but guidance for practical implementation is often lacking. Our effort involves a multi-faceted approach, primarily focusing on the integration of smart contracts within the Node-RED[1] environment, a development tool for connecting hardware devices, APIs, and online services in new ways. The basic requirements for the solution are enhanced security, while speed and user-friendliness are not compromised.

This paper also focuses on the use of blockchain in academic and research environments, the authentication of research data, and the potential of this technology in the context of a metaverse environment. The metaverse is defined as the connection of the virtual world to the real world, which occurs through the use of IoT devices. Consequently, the management of IoT devices is the next area of focus. The article is structured as follows. Section 2 reviews common security flaws associated with IoT devices and the usage of blockchain to limit those flaws. Section 3 contains a description of the proposed usage of blockchain and the description of technologies used. Section 4 describes the implementation results with emphasis of the smart contract deployment and the description of proposed approaches to using blockchain in IoT. In section 5, the drawbacks of blockchain usage are discussed.

2 REVIEW

In the realm of IoT, security is a primary concern. IoT devices often collect and disseminate sensitive information, making them vulnerable to cyber-attacks. The inherent security attributes of blockchain technology, such as cryptographic encryption and decentralized data storage, play a pivotal role in fortifying this data (Dorri et al., 2017).

Several scholars have contributed to the understanding of these vulnerabilities. Unwala et al. (2018) discuss the critical period when a new device joins an IoT network, highlighting the necessity of robust authentication processes to prevent unauthorized access. They delve into the security features across various IoT protocols, such as Z-Wave and Thread, to underscore the complexity and depth of security measures required.

Additionally, Dragomir et al. (2016) examine the security capabilities of established IoT communication protocols and emphasize the need for standardized, interoperable security solutions to protect against increasingly sophisticated threats. This paper stresses the importance of industry collaboration and standardization efforts by groups like the IEEE and IETF to fortify IoT security.

The evolving nature of IoT security threats is further highlighted by Parashar and Rishishwar (2017), who discuss how the interconnectedness of IoT devices facilitates rapid information exchange but also increases susceptibility to hacking and service disruptions. Their research calls for scalable security solutions that do not compromise the operational efficiency of IoT systems.

[1] Available at `https://nodered.org/`.

Recent research also identifies specific modern threats to IoT environments, such as Distributed Denial of Service (DDoS), Man In The Middle (MITM), and replay attacks, which exploit the inherent vulnerabilities of IoT devices attacks (Dorobantu and Halunga, 2020; Lalit et al., 2022; Rajendran et al., 2019).

These studies underscore the complexity of IoT security and the need for a multi-layered approach to protect against both current and future threats. To address these threats, various security measures have been proposed, including lightweight security models and techniques, and countermeasures against potential attacks (Dorobantu and Halunga, 2020; Lalit et al., 2022; Rajendran et al., 2019).

Traditionally, IoT networks have been dependent on centralized models for data processing and storage, potentially engendering single points of failure. Blockchain, as a decentralized mechanism, obviates these vulnerabilities, thereby augmenting the reliability and robustness of IoT networks. This decentralization concurrently diminishes the risk of service interruptions, ensuring continuous operation (Dorri et al., 2017; Hosseini et al., 2023; Polat, 2023).

In the context of IoT, blockchain serves as a tool to secure integrated devices and their communication. It is used to authenticate devices on the network, where each device can have its own unique identifier in the form of a blockchain address. This address is used to secure communication between devices and to verify their transactions (Dorri et al., 2017).

The decentralized nature of the blockchain means that data is not stored in a single location, which eliminates the risk of attacks on individual data stores and increases the resilience of the network against outages. This is critical for IoT applications (Hosseini et al, 2023). Each transaction inscribed onto a blockchain is immutably recorded in a tamper-resistant manner, which significantly reduces the likelihood of data misuse. Blockchain technology not only guarantees the integrity of the data collected and disseminated by IoT devices, but also preserves the quality and reliability of the data, which is essential for decision-making processes in various industries (Polat, 2023; Ramesh et al., 2020).

Blockchain also enables the implementation of smart contracts, which are programs stored on the blockchain, triggered automatically when defined conditions are met. Within the IoT sphere, smart contracts can autonomously manage processes and interactions between devices, eliminating the need for human intervention. For instance, a smart thermostat could autonomously request and remunerate for heating oil as required, with the transaction securely recorded on a blockchain. Similarly, in the context of our project, it could authenticate access to smart locks on doors (Zheng et al., 2017).

The use of blockchain together with IoT has been explored in many papers. The authors in (Dorri et al., 2017) propose a novel blockchain-based architecture designed to provide lightweight, decentralized security and privacy for IoT without the overhead typically associated with blockchain technology. Their architecture is structured hierarchically and includes smart homes, an overlay network, and cloud storage, which coordinate data transactions using blockchain to ensure privacy and security. This architecture utilizes different types of blockchains depending on the network tier, which helps in reducing latency and computational demands that are typical in standard blockchain operations. The smart home tier uses a localized blockchain that requires no Proof of Work, thus, conserving resources. The overlay network facilitates data transactions between smart homes and external services with reduced overhead and increased privacy through clustering and selective transaction verification.

The paper from Alam (2019) discusses the integration of blockchain technology with the Internet of Things (IoT), focusing on how blockchain's secure, decentralized ledger enhances data security and communication among diverse, smart IoT devices, while also exploring the opportunities and challenges of this approach.

Belhadi et al. (2023) describes a blockchain-based system for improving security and efficiency in medical image segmentation within the Internet of Medical Things, using ensemble learning, genetic algorithms, and U-Net architectures, resulting in enhanced performance

and robust security. In the case of security testing, blockchain has proven to be a reliable technology. It is mainly secured by asymmetric cryptography, where every operation to write to the blockchain or call a smart contract must be signed with a private key. This private key is typically encoded in a blockchain wallet, which also has a public key from which the wallet address is generated (Rawat et al., 2021).

Further proof that blockchain's significantly enhance IoT security, offering practical insights into blockchain's role in strengthening IoT access control mechanisms, is provided by Singh et al. (2023). In the paper, blockchain technology is applied to IoT access control, focusing on preventing cyber-attacks. It reviews various blockchain platforms for secure IoT access control and evaluates the efficacy of smart contracts in addressing security issues.

Sandner et al. (2020) depicts the synergistic use of blockchain, IoT, and AI, showcasing how blockchain ensures secure and transparent handling of IoT data, while AI analyzes this data for advanced decision-making.

Various applications across domains like smart agriculture, smart grid, smart home, smart transportation, banking, and finance are described in Tyagi et al. (2023). The paper also delves into the role of smart contracts and their functional architecture in these environments.

While these studies illustrate the broad applicability of blockchain in enhancing IoT security across various domains, the specific challenges and requirements of smart homes necessitate focused research. Smart homes are unique due to their integration of diverse, interconnected devices within a personal living space, requiring seamless and secure communication. This domain's specificity means that while general principles from other IoT applications can inform smart home security, dedicated solutions addressing the unique vulnerabilities and operational demands of smart homes are essential.

This paper focuses specifically on the role of blockchain in smart homes. For the implementation the smart contracts will be used. Finally, other technologies used in the practical part of the paper will be described.

2.1 Integrating Blockchain in Smart Homes for Enhanced Security and Automation

Smart homes, as the term suggests, are residences equipped with advanced technologies that enable automation and enhanced control over various home functions. These technologies encompass a range of applications such as energy management, healthcare, security, and automation of household tasks. Smart homes utilize IoT devices to monitor, control, and support residents, thereby improving their quality of life and promoting independent living. The key focus of smart home technology is to provide tailored services to users, optimizing comfort, efficiency, and safety within the home environment (Madakam and Ramaswamy, 2014).

Several security and privacy risks and challenges in the IoT, particularly in smart homes are identified in El-Azab (2021). These are the same security threats mentioned in the previous articles mentioned in the general IoT field.

Another article from Tyagi et al. (2023) proposes a new smart home gateway network architecture using blockchain technology. The proposed network is divided into three layers: device, gateway, and cloud, with blockchain employed at the gateway layer to ensure data integrity and security. The paper includes an experimental analysis demonstrating the effectiveness of this architecture over traditional centralized models.

Most of those and other articles that discuss the use of blockchain in smart homes make use of the Ethereum blockchain, as the most widely used and verified platform (Teutsch and Reitwießner, 2019).

2.2 Blockchain Platforms

In the context of our research, the comparison of multiple blockchain platforms to identify the most suitable one was performed. The analyzed platforms included Ethereum, Solana, Cardano, Polkadot, Bloxberg, Hyperledger Fabric and Binance Smart Chain (BSC). For each of these platforms, several factors such as algorithm

Tab. 1: Blockchain Platforms Comparison

Platform	Blockchain type	Algorithm	Theoretical speed (transactions per second)	Smart contract language
Ethereum	Public	Proof-of-stake	Dozens	Solidity
Cardano	Public	Proof-of-stake	Hundreds	Plutus
Solana	Public	Proof-of-history	Thousands	Rust
Bloxberg	Public	Proof-of-stake	Dozens	Solidity
Binance Smart Chain	Public	Proof-of-authority	Hundreds	Solidity
Hyperledger Fabric	Private	Pluggable consensus protocols	Thousands	Standard programming languages
Polkadot	Public	Nominated Proof-of-Stake (NPoS)	Thousands	

consensus, programming languages, transaction speed, cost of operation, and decentralization were considered.

Ethereum proved to be a very robust and reliable platform, mainly due to its Turing-complete programming language Solidity and strong developer community. It has switched to a proof-of-stake algorithm, reducing its energy consumption and increasing throughput. Ethereum is also compatible with a variety of tools and has great support for smart contracts and non-fungible tokens (NFTs). Solana, on the other hand, offers extremely high transaction speed thanks to its proof-of-history algorithm and sharding technologies. However, it faces security challenges and frequent outages, which reduce its reliability.

Cardano, like Ethereum, uses proof-of-stake and is known for its formal approach to development and scientific methodology. Its unique Ouroboros consensus system guarantees high scalability. Nevertheless, Cardano is not yet as stable and proven by various practical implementations. Binance Smart Chain combines proof-of-stake and proof-of-authority, which ensures high speed but also lower decentralization. Polkadot enables interoperability between different blockchains through its parachains, supporting a wide range of decentralized applications. However, neither Polkadot nor Binance Smart Chain are yet sufficiently stable and proven by various practical implementations, which limits their applicability for our project.

The Binance Smart Chain has proven to be a fast and reliable blockchain, but it is a network that is largely controlled by the commercial cryptocurrency exchange Binance. It is thus a blockchain that is largely centralized and thus could be unstable (Han et al., 2021). For the purposes of this research, it therefore appears unsuitable.

The same is true, although to a lesser extent, for the Cardano and Solana platforms. Ethereum's robust features, widespread adoption, and consistent updates make it sufficient for complex, long-lasting blockchain applications, also for the research projects. Bloxberg, originated as a fork of Ethereum, is more focused on experimentation in the academic sector.

3 METHODOLOGY

Based on the research above, the Bloxberg was selected as the most suitable platform for our project. Bloxberg is specifically adapted for academic purposes and uses proof-of-authority, which increases efficiency. It was developed by the prestigious German research organization Max Planck Society and has strong support from other major academic institutions. Thanks to its compatibility with Ethereum, it allows the use of smart contracts written in the Solidity language and other features from the Ethereum blockchain. This platform is ideal for secure

and transparent storage and management of research data, which is crucial for our needs. Bloxberg also guarantees a high level of security and data integrity, which is essential for our project.

For our use case, smart contracts, programs stored on the Ethereum or Bloxberg blockchain that execute exactly according to code, are very important, eliminating the risks of outages, fraud, censorship, or outside interference. Their uniqueness lies in their capability to autonomously enforce predefined rules and penalties, similar to traditional contracts, but with added automation. In the realm of IoT, smart contracts have big potential for automating complex processes and interactions between devices, enhancing data integrity, and enabling new models of service delivery and automated decision-making, thereby revolutionizing IoT ecosystems with their self-executing and self-enforcing nature (Taherdoost, 2023; Antonopoulos and Wood, 2019).

Smart contracts are used in many fields, from Decentralized finance (Schär, 2021) or Academic and education sphere (Palma et al., 2019; Palma et al., 2020) to IoT (Lone and Naaz, 2021) and Smart Homes (Lee et al., 2020).

For writing smart contracts, Solidity language (2024) is used. It exemplifies a high-level, statically-typed programming paradigm. The Solidity design facilitates the implementation of self-enforcing business logic within smart contracts, ensuring immutable transaction records. Since Solidity is a very recent language, it is important to be aware of the security issues and threats that Solidity often suffers from, as mentioned in (Staderini et al., 2022).

For writing code and then testing and deploying smart contracts, the Remix IDE is used. REMIX IDE is an open-source, web-based integrated development environment specifically designed for Ethereum smart contract development. It facilitates the writing, testing, debugging, and deployment of smart contracts in Solidity. Key features of REMIX IDE include an integrated debugger, static analysis tools, and a user-friendly interface for deploying contracts on the Ethereum or Bloxberg blockchain. Its browser-based accessibility and comprehensive toolset make it ideal for both novice and experienced developers in the field of blockchain technology (Ethereum, 2024).

For more advanced testing and detailed analysis, Ganache is used. Ganache is a part of the Truffle Suite, serving as a personal, local blockchain for Ethereum or Bloxberg development. It allows developers to deploy contracts, develop decentralized applications (dApps), and run tests in a private, risk-free environment. Ganache provides key features like simulated blockchain transactions, contract execution, and block mining, with the flexibility of both a desktop application and a command-line tool (Ganache CLI). This tool is essential for developers to test and refine smart contracts before deploying them to the public blockchain network (Truffle Suite, 2024). For creating an architecture that connects IoT hardware devices, smart contracts, APIs, and other services (cloud and online services) it is appropriate to use Node-RED.

Node-RED is a popular open-source tool used in IoT and home automation. It offers a visual programming interface that simplifies creating applications and automation flows, even for those without extensive coding knowledge. Users can easily connect and control data and devices using pre-built blocks called nodes, which are connected to define data flow. These nodes support various functionalities and communication protocols like MQTT and HTTP, allowing integration with a wide range of IoT devices and services. Node-RED also facilitates real-time monitoring and debugging, making it easier to optimize workflows. It's versatile in deployment, running on platforms from Raspberry Pi to cloud services.

To be able to integrate smart contracts into this tool, an in-depth exploration of the capabilities of Node-RED was performed. This process was twofold: first, it involved a thorough examination of the various libraries and modules available within the Node-RED ecosystem that facilitate communication with blockchain networks. Second, a practical implementation of smart contracts in the Node-RED environment was created.

Fig. 1: Node-RED is the central point for controlling IoT devices. A user may interact with Node-RED that is connected to Smart Contract to verify the user's access

After the research and design phase, the development phase followed. The code for the smart contracts was created. This code, formulated in Solidity using the Remix IDE, was explicitly tailored to manage the locking and unlocking mechanisms of door locks. The smart contract on the Bloxberg blockchain was deployed using the Remix IDE tool.

Upon the successful development, next phase was the integration of this code within the Node-RED environment, see Fig. 1. This stage was critical in bridging the gap between the theoretical aspects of smart contracts and their practical application in real-world scenarios. The process involved deploying the smart contract to a test blockchain network, an essential step for verifying the functionality and security of the contract under simulated conditions. For this deployment, the Ganache tool, which provided a streamlined and controlled environment for testing, was utilized.

Parallel to the deployment, the appropriate Node-RED flow was created. This flow was intricately designed to interact seamlessly with the deployed smart contract, thereby facilitating the communication between the Node-RED interface and the blockchain network.

For our use case, a simple smart contract[2] showing the basic structure for securing access to a smart door was created. A new contract is deployed for each door, allowing for separate management. Thus, for each door, the contract may be slightly different and may contain different access rules. In a more complex system, there could be a single, large smart contract that also manages the individual IoT devices.

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4 RESULTS

4.1 Smart Contract Deployment

A smart contract that allows the owner to manage the list of users who have access to the home and allows these users to open and close door it the home based on their permissions was created. Events are used to inform others of events in the smart contract.

The contract was deployed through Remix IDE. For testing purposes, Remix IDE provides a way to deploy the contract to the virtual blockchain that runs on local device. In case of and deployment of a contract on a production blockchain, the blockchain wallets in a browser, for example MetaMask, through which we can sign and confirm the deployment of this

[2]The whole contract is available at `https://github.com/AndrejGono/IoTBlockchainPaper/blob/main/SmartHomeAccess.sol`.

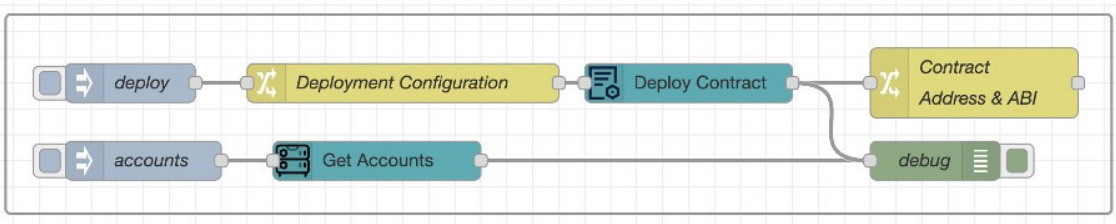

Fig. 2: A flow in NODE-RED for deploying a contract

contract needs to be integrated. However, the goal was to integrate this contract into Node-RED, so it was deployed automatically through the Remix IDE service.

To integrate the contract into Node-RED it was necessary to compile the contract in Remix IDE and find out what is its ABI (Application Binary Interface) and ByteCode, with which it will be possible to deploy the contract directly from Node-RED. The ABI acts as an interface between the smart contract and an external caller, such as applications or other contracts. ByteCode is a string of bytes that an Ethereum virtual machine (EVM) can execute. After writing and testing the code in Solidity, this code is compiled into ByteCode.

Ganache was used for contract deployment, which provides a local test blockchain on which the contracts to test transactions can be deployed.

In Ganache, it is necessary to create a new Ethereum or Bloxberg environment and Ganache will create a separate test blockchain, within which it will also create a list of Bloxberg addresses loaded with Bloxberg tokens. This blockchain is running on address *localhost* and port 7545.

Upon the creation of a contract and a blockchain for deployment, a new flow in Node-RED that deploys the contract automatically is also created (see Fig. 2).

This flow contains multiple nodes:

- Deploy: This node initiates the deployment process, serving as the control input that starts the operation when activated. This Note could be replaced by an HTTP Request node, which allows the contract to be deployed by calling a REST API endpoint.
- Deployment Configuration: This node contains predefined parameters essential for the deployment process, like bytecode, ABI and arguments for contract constructor.
- Deploy Contract: This node performs the deployment of the contract, executing the process using the provided configuration details to launch the contract into the desired environment.
- Contract Address & ABI: This node outputs the contract address and ABI, which are essential for interfacing with the deployed contract, providing a means for applications and users to interact with it.

Once a contract has been deployed, a flow is created that allows the methods of that contract to be called. Two HTTP endpoints are provided for users to call, thereby opening and closing doors. It is assumed that the user who calls this method has the necessary permissions to control the door. This flow can be seen in Fig. 3.

- [post] */open:* This HTTP input node listens for POST requests on the /open endpoint. When a request is received, it triggers the

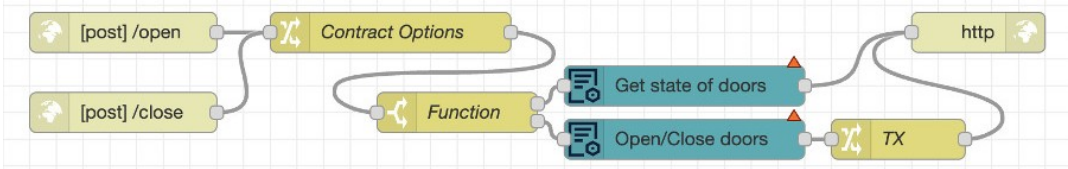

Fig. 3: A flow in Node-RED for calling functions to open and close the doors

flow to call a function on the smart contract that checks whether the provided address has access rights. If access is granted, the function will proceed to open the doors.

- Contract Options: Configures the necessary parameters to interact with the smart contract, such as the smart contract's address, ABI, gas limit for Ethereum or Bloxberg transactions and also translates http body attributes to flow attributes, so other nodes know what to do.
- Function: This node constructs the transaction object to interact with the smart contract. It contains the logic to call the 'open door' function within the smart contract, which includes specifying the function name and arguments based on the incoming request data.
- Get state of doors & Open/Close doors: These nodes execute the interaction with the smart contract. Since the 'open' action involves changing the state (by granting access and opening the door), it would utilize the Open/Close doors node to initiate a transaction on the blockchain. If there's a 'call' to simply check the status of blockchain without changing the state, it would go through the Get state of doors node.
- TX: This node is set to process the transaction. It would handle the transaction response from the blockchain network, or event trigger which includes a transaction hash or additional information.
- HTTP: This node sends the HTTP response back to the requester. It would communicate the outcome of the request, indicating whether the door was successfully opened or if the request was denied.

The corresponding process for closing the door would be similar using the close endpoint.

4.2 Proposed Secured IoT Approaches using Blockchain

It is logical that adding security measures will reduce the speed and user-friendliness of the solution. Our implementation contains a simple process where the user calls an HTTP endpoint on some server via a web or mobile app, which then calls a function on the IoT device. In our case, the smart doors that are opened or locked by the call. We have included an intermediary in this process, which is the blockchain, or smart contract, which is deployed on this blockchain and serves as middleware. The smart contract performs an additional verification that the user with the blockchain address through which this contract calls has indeed been granted permissions. In this case, the blockchain acts as a database in which the blockchain addresses of users are stored, and each one is assigned information about whether it has access to a given door. Communication through this intermediary logically slows down the whole process, because the blockchain acts as a robust and secure, but slow, database. Much depends on the use of the particular network. The Bloxberg, which is one of the fastest networks because new blocks are created in it and added to the network every 7 seconds was used. Every transaction, and therefore call or operation performed by a smart contract, is stored in a block within a maximum of 10 seconds, and thus is forever written in the history of the blockchain.

In order to assess the efficacy of proposed approaches, a solution that makes use of blockchain was put in a contrast with a solution that does not. Concurrently, a balanced approach that would permit the utilisation of blockchain and its advantages while maintaining user-friendliness and simplicity was proposed. This balanced approach is an application that employs blockchain, wherein transactions are not signed by end-users, as is customary, but rather, the private key for signing transactions is stored on the server that users interact with.

Three variants for architecture have been proposed: 1) an application without the use of blockchain; 2) an application using blockchain, where users sign the transactions themselves; 3) an application using blockchain where the server signs the transactions.

The architecture of each solution can be seen in Fig. 4.

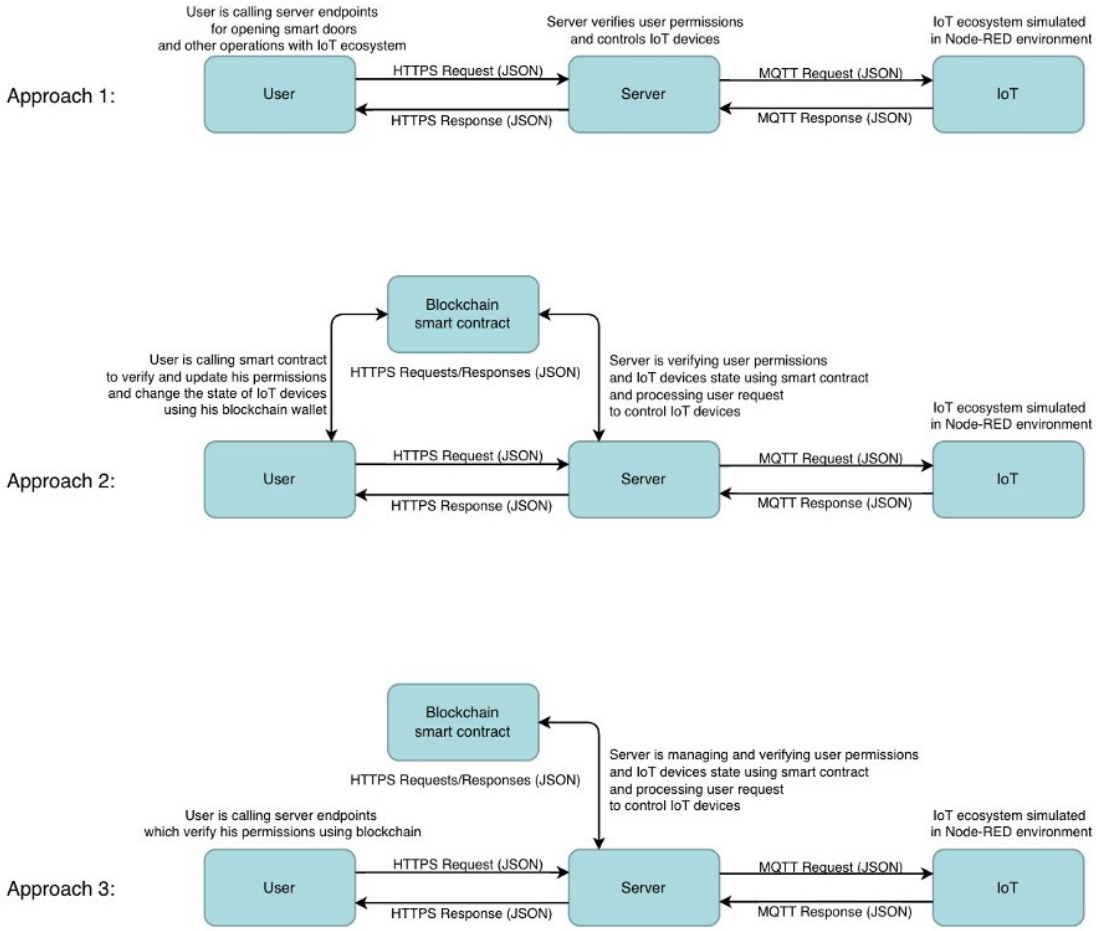

Fig. 4: The architecture of proposed solutions

The approach 1 is a standard communication model, without the use of blockchain. This approach is fast, but not as secured as when using blockchain.

The approach 2 is using blockchain, where each user has their own blockchain wallet, which they manage and protect themselves. This approach is very secure but slow and thus not suitable for dynamic things like smart doors. On the other hand, this approach is optimal for more tech-savvy users and for a sensor that does not store data very often (e.g. only once per hour). However, this complicates the whole process because it introduces an extra step. In order to interact with the blockchain, the user must download a wallet. When calling a smart contract, the user must provide his blockchain address and sign this operation with his private key. This work is handled for the user by their blockchain wallet, such as Metamask, which is open-source and generally considered secure and reliable. However, the user has a large number of other wallets to choose from. For some users, however, this may be a no-go, as they will not have the technical knowledge to operate the blockchain wallet and sign transactions through it.

The approach 3 is focused on an alternative to usage of blockchain. The users use a classic API and authentication via the blockchain is performed by the server.

To test the security of the approach, the call to a transaction with the user's address was signed with a different, custom private key.

In this case, the node does not accept the transaction at all and rejects it with an error message. This is because authentication works on the principles of asymmetric cryptography, where the blockchain address serves as the public key (it is an encrypted public key) and each blockchain wallet has its private key encrypted belonging to it. Thus, in order to impersonate another user, their private key would have to obtained. The key is stored securely on the user's device and is managed by the wallet or blockchain application they use.

4.3 User Testing of the Designed Application

As stated in the introduction, the primary objective of the proposed solution is to enhance the security of the system through the utilisation of blockchain technology, while maintaining the user-friendliness of the system. As previously outlined in the research, the utilisation of blockchain introduces an additional intermediate authentication step to the overall system, thereby enhancing the overall security. However, this intermediate step results in a more complex and time-consuming process within the application, for example, when unlocking a smart IoT door.

Consequently, user testing was conducted to ascertain whether typical users would be able to utilise and operate a blockchain application without the experience being negatively affected. Additionally, the objective was to ascertain whether individuals lacking familiarity with blockchain or the technology in question would be able to utilise the blockchain application. Furthermore, the testing was designed to ascertain user perceptions regarding the use of blockchain in terms of security and the time required to complete the process. As the blockchain authentication process comprises a number of distinct stages, the testing also sought to ascertain which of these stages proved most challenging for users and which constituted a barrier to their engagement.

A total of 43 respondents participated in the testing phase. All participants were required to solve a hypothetical scenario in which they are in possession of a door equipped with an Internet of Things (IoT) lock, which they are able to control via a mobile application. A prototype of the mobile app was created in Figma, in which the entire process was simulated. Users were required to operate the app iteratively in order to complete the process of unlocking and opening the door.

The respondents represented the productive segment of the population, aged 20 to 60. They were categorised according to their educational background as follows: college technical (STEM), college non-technical (humanities), and no college degree.

A control group of ten respondents was tasked with unlocking an IoT door in an application without utilising a blockchain. In the context of the proposed solutions, this constituted Approach 1, which is commonly employed in classical blockchain-free solutions, whereby the user controls the IoT device by connecting to a server. The application is illustrated in Fig. 5.

The remaining 33 respondents were provided with a prototype mobile application, which was an implementation of the proposed Approach 2. This approach was selected due to its robust security and comprehensive user experience, which increases the potential for user error during the door unlocking process. The rationale behind the robust security measures is that the user retains control of the entire process, eliminating the need to delegate any functions to the server. This approach is therefore recommended.

The IoT door unlocking process with blockchain commences in a similar manner to the process without blockchain, but involves a few additional steps. These supplementary steps can be observed in Fig. 6.

In the initial phase of blockchain-based authentication, the user was required to select the appropriate blockchain wallet with which to sign the transaction. The signing of the transaction was conducted in a separate application, which is the reason for the discrepancy in visual style between the second and fourth screens in Fig. 6. This is a distinct application, designated as Metamask, to which the user was redirected.

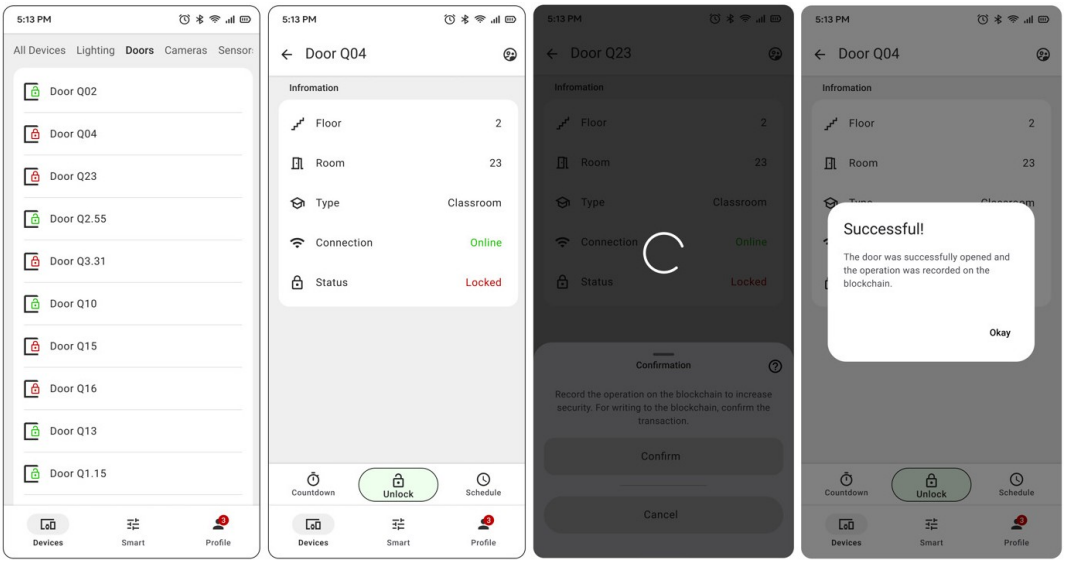

Fig. 5: Application for user testing with Approach 1 (without blockchain)

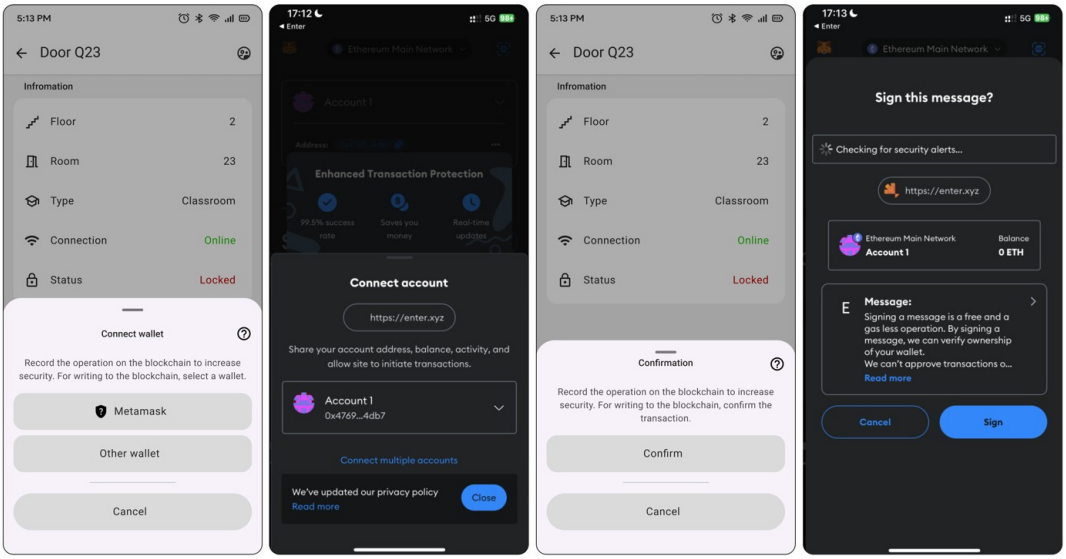

Fig. 6: Application for user testing with Approach 2 (with blockchain)

The wallet is capable of accommodating multiple accounts. The specific account is selected by the user on the second screen of Fig. 6. Following the selection of the account, the user is prompted for confirmation, as illustrated on the third screen. Upon confirmation, the user proceeds to sign a transaction, which is a smart contract on the blockchain, to verify their permissions (see Fig. 4).

4.4 Evaluation of Testing

Of the 33 respondents included in the test group, 32 were able to complete the entire verification process. Of the 33 respondents, 14 were previously unacquainted with blockchain technology, having no prior awareness of it. Another 12 respondents had heard of blockchain technology but had not utilized it.

A total of 13 respondents from the test group indicated that they had not completed a college education. A further four respondents held a non-technical college degree.

Given this data, the use of blockchain appears to be suitable for people without a university or technical education, and also for people without any experience with blockchain.

The average completion time for the process in the group that did not utilise blockchain technology was 19.7 seconds. In contrast, the group that employed blockchain technology and was required to undergo multiple verification steps took, on average, 59 seconds to complete the process. The entire process was completed in a maximum of 120 seconds. This is, therefore, almost three times longer.

For this reason, respondents in the blockchain group were asked how they perceived the process in terms of time. Only one respondent, out of 33, found the process to be very efficient, stating that it was fast and minimally time consuming. 12 respondents considered the process to be efficient, stating that it was relatively quick and that the time invested was reasonable. 12 respondents considered the time to be less efficient, indicating that although the process was longer than anticipated, it was still manageable. Conversely, 7 respondents considered the time to be inefficient, indicating that the process was too long and that the time invested was unreasonable.

The time required to complete the process has an adverse effect on the user-friendliness of the application, which may ultimately discourage users from utilising it. In light of the fact that there is no means of accelerating the verification of a transaction on the blockchain, it is evident that none of the aforementioned steps can be circumvented. Consequently, there is limited scope for improvement. Further testing would be required to ascertain whether users are willing to accept this time frame. In the event that they are not, we recommend utilising Approach 3 (see Fig. 4), whereby a portion of the process is conducted on the server, thereby reducing the overall time required for the user.

In order to ascertain whether users would be amenable to an extension of the allotted time, respondents were invited to provide their assessment of the application in terms of its user-friendliness. A total of 29 out of 33 respondents rated the application as excellent, good, or fair. Four respondents provided negative ratings, citing a lack of understanding and the difficulty of the process, not just the blockchain component, as the primary reasons for their assessment. These respondents had no university degree and no experience with IoT and blockchain technologies.

Additionally, while testing, users were afforded the opportunity to access the app's help functionality should they require clarification regarding the appropriate course of action in a given scenario. The tooltip provided an explanation of relevant blockchain terminology, facilitating a more comprehensive understanding of its advantages. However, only 10 respondents availed themselves of this assistance. The majority of respondents demonstrated sufficient understanding to complete the process independently, even if they lacked prior experience with blockchain.

5 DISCUSSION

Adding blockchain as an intermediary in the process of controlling smart doors has increased security at the expense of speed and user-friendliness, which is in line with expectations. Performance testing has shown that each transaction through the blockchain takes a minimum of 7 seconds, which may be limiting for some applications.

Performance testing is usually done using load tests, where a method or process is run many times in a row, and latency and response time are monitored under this increased load. However, such testing is more challenging in the case of blockchain testing because the same transaction (or smart contract call) from a single blockchain address to the blockchain

can only be send once per block. A second transaction can only be send after the previous transaction has been included in the block and that block has been verified by the blockchain node the application is communicating with. This means the user can call the smart contract method only once in each block, that is, only once every 7 seconds. This is a common security measure of most cryptocurrencies, where the possibility of sending multiple transactions in a single block could lead to multiple spending of identical funds. Thus, in practice, there will never be an "overload" of blockchain requests from a single user.

However, it may happen that thousands of users will interact with the blockchain or a certain smart contract at one moment. This could significantly slow down the machine that processes the transaction, and therefore increase the waiting time of 7 seconds for a transaction to be executed significantly. Again, this is virtually impossible to test because the blockchain itself runs on a large number of nodes, and it is never know which node a user will be communicating with. Ideally, the user communicates with the closest node, but the blockchain also tries to distribute the network communication among the other nodes. How a given node handles the load depends on its hardware parameters, and of course each node is different. However, blockchain networks, whether Bitcoin, Ethereum or Bloxberg, work on the principle that they contain what is called a mempool, which is a small database containing transactions to be included in a new block and verified. If a blockchain node receives more transactions than it can include in a block, it simply stores the remaining transactions temporarily in the mempool and verifies them in the next block.

Again, it is not possible to determine the exact number of transactions that will fit in a single block. Bloxberg, like Ethereum, does not have a fixed limit block size in megabytes, like Bitcoin, for example. Instead, it uses the concept of "gases", where each transaction costs a certain amount of gases depending on what computational resources are needed to execute it, and each block has a gaseous limit that determines how many transactions can fit in it. The gas limit for a block changes dynamically depending on the decisions made by the miners (in the case of Proof-of-Authority on Bloxberg, the universities make the decisions) and the current network. The gas limit for a block is in the range of millions of gas units. The typical gas limit per block is around 15 million gas. A simple transaction as well as our transactions for locking/unlocking doors have around 21,000 gas. This means that theoretically, if a block contained only simple transfer transactions, a block would fit approximately 714 transactions (15,000,000/21,000 = 714). In practice, however, blocks contain a mix of different transaction types, and the actual number of transactions in a block will depend on their specific complexity and the amount of gas used. In situations where data retrieval from the blockchain is the sole objective, waiting for a new block is unnecessary, and immediate access to the data is available. However, in the context of the paper and in the majority of cases, there is an additional requirement to write data to the blockchain. For instance, after unlocking or locking a door, it becomes necessary to record its current state on the blockchain. Unfortunately, in such scenarios, users must patiently await the inclusion of this operation in a block. What can be said for sure is that each user transaction takes a minimum of 7 seconds. If the network is congested and the nodes cannot keep up with adding all new transactions to a block (the blocks are full), the user may wait several times longer for a transaction. If the user should wait longer than a few seconds to unlock the door, such an application does not make sense and will certainly not be accepted by the normal user. A solution could be the use of private blockchains, in which new blocks would be included in the block more frequently.

6 CONCLUSION

This research demonstrated the effective integration of blockchain technology with Internet of Things (IoT) devices, focusing on securing access control in smart homes, specifically through smart door locks. The practical application involved using Bloxberg smart contracts within the Node-RED environment to enable secure and autonomous control of smart door locks. This integration showed a substantial improvement in IoT security, leveraging tools like Remix IDE and Ganache for smart contract development and testing.

The principal contributions to the field are the results of the user testing. The user testing, which involved 43 participants, revealed that 97% of users could complete the blockchain-based verification process within an average time of 59 seconds, indicating that it is a feasible technology for real-world applications. Regardless of their technical background, users were able to operate the blockchain-enabled app with proficiency.

Three architectural approaches for integrating blockchain with the Internet of Things (IoT) were put forth for consideration. A solution that does not utilise blockchain technology, a fully decentralised user-managed blockchain solution and a blockchain solution that is assisted by a server.

The fully decentralised approach offers robust security, but it can be complex and time-consuming for users. The server-assisted approach strikes a balance between security and usability by offloading certain processes to a server, thereby rendering it more practical for everyday use. The findings indicate that blockchain-based applications have the potential to improve the security of IoT systems without negatively impacting the user experience. The server-assisted approach, in particular, represents a promising solution for industries seeking to develop secure and user-friendly IoT applications.

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EMPIRICAL EVIDENCE ABOUT EARNINGS MANAGEMENT BEHAVIOUR UNDER THE COVID-19 PERIOD IN ALGERIAN COMPANIES

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ABSTRACT

This study explores the influence of the Covid-19 period on earnings management behaviour (EM) for 150 Algerian companies. The period of study (2018 to 2021) was divided into the pre-pandemic period (2018 and 2019) and the pandemic period (2020 and 2021). The study used two measures for earnings management: discretionary accruals (accounting EM) and abnormal cash flows (real EM). The results indicate that accounting EM decreased during Covid-19 compared to pre-Covid-19. But for real EM, it was the opposite; it has seen an increase during Covid-19. These results have many implications regarding the commitments of various contributors to preparing financial information and other related parties to ensure the accuracy of financial reporting during periods of crisis. More specifically, accounting standards setters should issue additional explanations regarding the accounting for some items, and auditors should extend the range of verification when certifying financial statements.

KEY WORDS

earnings management, discretionary accounting accruals, abnormal cash flows, Covid-19 period

JEL CODES

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1 INTRODUCTION

For a long time, the years 2020 and 2021 have been the most difficult for economies and businesses around the world due to the Covid-19 outbreak, which required many procedures to be put in place, including closure and social distancing as mechanisms to limit the spread of the Coronavirus disease. As a result, many industries and activities have been paralysed or restricted, and the operations of many companies have been disrupted, which has deteriorated the financial performance of companies and threatened their sustainability (Aljawaheri et al., 2021).

KIMOUCHE, Bilal, and BOUSSENNA, Hemza. 2024. Empirical Evidence About Earnings Management Behaviour Under the Covid-19 Period in Algerian Companies. *European Journal of Business Science and Technology,* 10 (2): 242–257. ISSN 2694-7161, DOI 10.11118/ejobsat.2024.007.

Algeria is not isolated from the outside world; the Ministry of Health, Population and Hospital Reform reported the first cases of infection since February 2020. Therefore, Algerian authorities imposed quarantine measures and a long period of total closure in 2020, followed by short periods of partial closure in 2021, to limit the pandemic outbreak. The challenge for companies was the government requirement to keep only 50% of employees, with exceptional paid leave for the rest, which increased their working capital requirements. These measures have created unfavourable circumstances for companies due to restricting their activities and disrupting several industries. Consequently, many Algerian companies experienced difficult times regarding solvency and liquidity, which menaced their going concern. The macroeconomic situation was not much better, with declines in all economic indicators exacerbated by lower oil prices.

The Algerian government has introduced many incentive measures to reduce the consequences of the limitation measures against the Covid-19 outbreak. However, the difficult economic situation known by Algeria since 2015 due to the volatility in oil prices prevented any direct intervention, which confined some monetary and tax measures. On its side, the tax administration delayed the filing date for income taxes and deferred tax obligation payments by companies until the containment period, so companies will not be subject to sanctions or penalties. Regarding the fulfilment of work and services according to the contracts, the government required cancelling the contractual deadlines and not applying financial penalties for delays (KPMG, 2020).

The Bank of Algeria has reduced the legal reserve ratio for banks from 10% to 8% and the minimum liquidity threshold from 100% to 60%. It was also imposed on banks and financial institutions to defer or renew the maturities of loans due at the end of 2020 or after. Furthermore, the Bank of Algeria gave instructions for extending the deadlines for the use of appropriations, delaying the due payments, and cancelling the late penalties for receivables due at the end of 2020 or after, in addition to maintaining or renewing operating credit lines (KPMG, 2020).

Covid-19 had a substantial negative influence on companies' results due to lower demand and difficulties in doing business, which directly impacted profitability, liquidity, credit quality, and the supply chain. Accordingly, companies might want to develop their reporting strategies under the uncertainties relating to these effects (Hidayat et al., 2022). The Covid-19 pandemic has severely impacted all countries, leading to a global recession that has been described as the worst since the 1930s (Nazmul and Sayma, 2022).

According to Hassan (2023), the nature of the business and institutional environment in which companies operate affects their financial reporting choices. He indicated that Saudi companies' accounting choices towards aggressiveness or conservatism during the pandemic were consistent with political cost theory and transaction cost theory. Nazmul and Sayma (2022) estimated that 46% of companies were probably manipulating earnings during the Covid-19 period. Overall, most studies agree that managers become more involved in earnings management during troubled periods. However, their goals tend to be controversial (Lassoued and Khanchel, 2021).

Earnings management includes all managers' accounting decisions to select and apply accounting policies and estimates (accounting EM), in addition to their real resource allocation decisions (real EM), including those that relate to operating, financing, and investment activities (Kimouche, 2022). Due to the different properties of the two earnings manipulation techniques, managers can use them alternatively or simultaneously. In this context, Yan et al. (2022) pointed that in periods of lockdown, managers assess the cost-benefit relationship regarding each earnings management technique before adopting an accounting decision.

The literature identifies three perspectives for the choice of accounting policies by managers. The first perspective concerns managerial opportunism, where managers adopt accounting policies that maximise their private interests (bonus plans, reputation, etc.). The second

depends on the contractual perspective, where managers tend to select accounting policies that reduce contractual costs. The third perspective concerns the informational view, where accounting policies are used to transmit private information or send signals to related parties about the company's future performance (Kimouche, 2021; Hassan, 2023). However, crisis periods can add additional dimensions or change managers' preferences towards these perspectives (Hassan, 2023).

Yan et al. (2022) proposed three incentives for earnings management during the Covid-19 period. First, financial pressures arising from deteriorating working capital are causing companies to manipulate earnings to meet their financing needs. Second, managers can rely on earnings management consistent with the signal theory to convey good news to stakeholders about the company's prospects. According to Filipović et al. (2022), the economic turmoil generated by Covid-19 represents a motivation for companies to engage in accounting manipulation by increasing income to achieve a certain level of dividends. Third, uncertainty has serious influences on managers' financial policies, leading them to change their strategies, for example, by delaying or reducing investment projects.

Poor performance can create incentives for earnings management. When companies perform poorly during difficult times, managers may want to signal recovery and improvement by manipulating earnings (Yassin et al., 2022; Jordan et al., 2021). Moreover, managers seek to increase earnings in order to hide losses and thus avoid negative perceptions from stakeholders or meet their expectations as a way to facilitate access to financing and avoid liquidity risks (Rusmianto and Makhsun, 2021; Hariadi and Kristanto, 2022; Hidayat et al., 2022).

According to Usheva and Vagner (2020), unexpected environmental changes lead managers to reconsider their resource allocation. Therefore, manipulating accounts to create savings is a strategy to maintain business continuity during difficult times and obviate bankruptcy. The effects of Covid-19 require directors to respond instantly to achieve a habitual level of performance or at least maintain the going concern of the company (Hariadi and Kristanto, 2022; Hidayat et al., 2022).

Some studies have found that companies are expected to excessively manipulate their earnings during downturns and financial distress to avoid institutional supervision and government monitoring (Xiao and Xi, 2021). According to Flores et al. (2021), companies in emerging economies have a tendency to exercise more earnings management in the Covid-19 crisis to reduce taxes because of the small margins for governments to adjust taxes and the structural economic fragilities. Furthermore, the Coronavirus could provide more incentives for companies to practise earnings management by reporting lower earnings to present themselves as potential recipients of government aid or to avoid regulatory attention.

Other studies have proposed potential techniques for earnings management during the Covid-19 period. Ozili (2021) expected that some techniques of accounting manipulation, such as income smoothing, loss avoidance, and big bath accounting, could mitigate the negative influence of Covid-19 on the company's financial position and performance. Hidayat et al. (2022) stated that some companies report higher quarterly earnings than they realise by reducing reported losses and deferring asset impairment charge-offs.

Contrarily, companies could manage their earnings by excessive recognition of impairment losses during the Covid-19 pandemic to write off bad assets as a tool to enhance future performance in line with the big bath accounting perspective (Flores et al., 2021; Dicken and Unger, 2021). Covid-19 may influence the amounts and timing of revenues and expenses, as well as the assumptions required to evaluate them, especially for contracts that extend over more than one period (Yassin et al., 2022).

Complementing previous research, the present study seeks to explore whether the Coronavirus crisis is changing the trend of Algerian companies towards earnings management. The study employs 150 Algerian companies during two years before the pandemic (2018 and 2019) and two years

during the pandemic (2020 and 2021). Following Kothari et al. (2005) and Roychowdhury (2006), the study uses discretionary accruals as a measure of accounting earnings management and abnormal cash flows as a measure of real earnings management, respectively.

Unlike previous studies, this study asserts that Covid-19 restricts accounting earnings management practices in Algerian companies, increasing the tendency of managers to perform more real earnings management as an alternative procedure.

The rest of this paper is organised into five sections: Section 2 develops the hypotheses starting from the literature; Section 3 displays the methodology; Section 4 summarises the results; and Section 5 presents the conclusions.

2 LITERATURE REVIEW

There is extensive empirical research about earnings management during difficult times; the most prominent are those relating to the 2008 financial crisis (Filip and Raffournier, 2014; Chintrakarn et al., 2008). Overall, these studies concluded that economic distress largely influences the tendency of directors to exercise earnings management, with conflicting interpretations. Nevertheless, this study follows the path of empirical studies on earnings management only during the Covid-19 period since early 2020. This review distinguishes four groups of studies according to the influence of the Coronavirus on earnings management.

The first group suggested that the pandemic has reduced earnings management. This group contains only the study by Rusmianto and Makhsun (2021), which measured discretionary accruals during and before the Covid-19 period and the effects of company size and gender management. The study was conducted among 15 Indonesian agricultural-listed companies during 2017–2020 and found that discretionary accruals were substantially lower in the Covid-19 period than before. Additionally, the study indicated that gender management and company size did not affect earnings management in either period.

The second group suggested that the Covid-19 influence on earnings management is limited, such as Jordan et al. (2021), who tested whether earnings management has resurfaced during the Covid-19 period in the United States. The study included 3,322 observations during 2020 and found no compelling evidence that earnings management occurred in 2020.

Ardiany el al. (2022) analysed tax avoidance and earnings management before and during the Covid-19 period for Indonesian-listed companies in the investment, trading, and services industries. The results showed that divergences between the pre- and Covid-19 periods regarding tax avoidance and earnings management were insignificant.

Azizah et al. (2022) investigated whether levels of accrual-based earnings management differed before and during the pandemic period (2019 and 2020) in Indonesian pharmaceutical companies. The findings showed that the pandemic did not affect earnings management, concluding that the pandemic does not necessarily motivate managers to manage earnings, especially for pharmaceutical companies that enjoyed relative prosperity during the Covid-19 pandemic.

The third group includes studies showing that earnings management behaviour has increased during the Covid-19 period. Starting with the investigation by Usheva and Vagner (2020), who found that the managers of Slovakian companies manipulated earnings in 2020 more than before to save amounts in the form of reserves since the consequences of the pandemic are not yet clear.

Dicken and Unger (2021) argued that European companies with negative performance manipulated earnings by reducing goodwill impairment losses during the pandemic. Ljubisavljević and Jakobsson (2022) suggested that managers of Swedish companies practised accounting earnings management to increase earnings in future periods. However, they observed no

significant change in real earnings management level due to the pandemic.

Aljawaheri et al. (2021) analysed the influence of the Covid-19 crisis on the manipulation of earnings and the sensitivity of share prices to earnings based on the financial data of 87 Iraqi-listed companies over the period 2018–2020. The results showed that with the Coronavirus outbreak, managers manipulated earnings to maintain their persistence, which decreased the quality of financial reporting.

Lassoued and Khanchel (2021) analysed the influence of the Coronavirus pandemic on earnings manipulation, using 2,031 companies listed on 15 European financial markets from 2017 to 2019 as the pre-pandemic period and from 2020 to 2020 as the pandemic period. They found that companies tended to manipulate earnings more during the Coronavirus period than before.

Flores et al. (2021) compared earnings management levels in the Covid-19 period among American and Brazilian companies, using 22,244 and 139,856 observations, respectively. They found that companies operating in emerging markets are more influenced by macroeconomic situations and tend to exercise earnings management during the Covid-19 period more than companies in developed markets.

Taylor et al. (2023) analysed the influence of the Covid-19 crisis on earnings management in 15 European countries. They used 399 quarterly observations in the pre-Covid-19 period (2019) and 768 quarterly observations in the Covid-19 period (2020–2021) for 105 listed banks. The findings showed a significant increase in earnings management during the Covid-19 period. However, they pointed that governance and audit quality limits the impact of earnings management and improves the quality of financial reporting.

Hariadi and Kristanto (2022) analysed the influence of the Coronavirus on earnings management with the moderating role of managerial capability history using 126 Indonesian-listed companies from 2018 to 2020. The results showed a positive influence of the Coronavirus on earnings management. Nevertheless, this impact can be diminished due to managerial capability history, where companies with managerial capability history tend to improve the quality of their earnings instead of engaging in earnings management behaviour.

Hidayat et al. (2022) conducted a study during and after Covid-19 and concluded that companies manipulating earnings experienced difficulties to maintain financial reporting quality and that earnings management is still being adopted to reassure stakeholders about the continuity of the company during the pandemic.

Ryu and Chae (2022) examined whether Korean service companies maintained accounting information quality during the Covid-19 crisis. The study included 580 observations during the pre-Covid-19 period (2018–2019) and 289 observations during Covid-19 (2020). The results indicated that companies practised real earnings management during the pandemic more than before, confirming the consciousness of managers about the uncertainty of future performance as the crisis continues.

Yassin et al. (2022) analysed whether managers in the United States and Jordan manipulated earnings during the Covid-19 period using a revenue standard. The study used an online survey in which 154 questionnaires were collected from US companies and 150 from Jordanian companies. The results suggested that companies in both countries manipulated earnings through the revenue standard during the pandemic.

Hsu and Yang (2022) analysed whether the Covid-19 pandemic influenced accounting quality and whether corporate governance mitigated this influence, using 3,122 observations from UK-listed companies. The findings showed that accounting quality was lower during the Covid-19 period as companies became more engaged in real earnings management. Furthermore, board size can moderate the negative influence of the pandemic on accounting quality.

Yan et al. (2022) investigated the Covid-19 crisis consequences on earnings management, employing 8,832 firm-years for Chinese-listed companies from 2018 to 2020. The findings revealed that the pandemic intensified real and accounting earnings management, especially in companies facing higher financial constraints.

The last group is distinct and includes only the study by Xiao and Xi (2021), which explored whether the pandemic has an influence on earnings management in China and the mitigating role of corporate social responsibility and external corporate mechanisms. The study included 2,029 listed companies in 2020 and suggested an expansion in accounting earnings management practices and a decrease in real earnings management. However, in companies with higher corporate social responsibility performance and higher audit quality, the levels of real and accounting earnings management were lower.

Contrary to previous studies and consistent with Xiao and Xi (2021) and Yan et al. (2022), this study tests the influence of the Coronavirus on real and accounting earnings management, since most previous studies only took into account the effect on accounting earnings management. This study was carried out in Algeria, where companies operate in a specific business and institutional environment that could affect their choices relating to financial reporting in different ways. Moreover, the impact of the disease on the Algerian economy and companies' performance has differed from that in other countries, which could affect managers' earnings management behaviour differently. Additionally, this study is among a few that included two years during the pandemic period and two years before, which may provide different evidence about the impact of downturns on earnings management.

From the literature, it appears that most studies found that periods of lockdown provide additional incentives to manipulate earnings, revealing different interpretations in harmony with the previously mentioned perspectives. Consequently, Covid-19 is expected to intensify earnings management practices in Algerian companies. Consistent with Anagnostopoulou and Tsekrekos (2017), this study expects a simultaneous employment of real and accounting earnings management during the Coronavirus period. For that, the study hypotheses can be formulated as follows:

Hypothesis 1: Covid-19 intensifies accounting earnings management in Algerian companies.

Hypothesis 2: Covid-19 intensifies real earnings management in Algerian companies.

3 METHODOLOGY AND DATA

3.1 Data Collection

The study used the financial data of 150 Algerian companies from 2018 to 2021, including 600 firm-year observations. The sample did not include financial companies due to their specificities concerning accruals and cash flow calculation. The random selection of companies depended on the financial statements' accessibility and the availability of all required information during all the studied periods due to the scarcity of databases containing financial data on Algerian companies, besides the smaller number of listed companies.

Moreover, most Algerian companies are public or family-owned; therefore, they do not face many disclosure requirements. Overall, Algerian companies suffer from high levels of secrecy and caution by managers regarding information disclosure, contravening corporate governance principles. We collected the required financial data from the National Centre for Commercial Register database (CNRC portal: `https://sidjilcom.cnrc.dz`), which is the sole database providing financial statements of companies operating in Algeria consistent with commercial law.

The sample selection considered large companies with sales of 2 billion DZD or more throughout the study, consistent with the investigation by the National Statistics Office (ONS, 2012). The initial sample included 1057 companies, divided into 515 state-owned, 451 privately owned, and 91 mixed-owned. All these companies prepare their financial statements under the National Accounting Plan (SCF), inspired by the 2003 version of IFRS. The rules of SCF require companies to apply all account-

ing policies of that IFRS version, including impairment tests, provisions, revaluation, etc., except for micro-enterprises employing no more than nine full-time employees, which apply simple accounting (cash accounting).

The only criterion used to select companies comprising the sample is the availability of their financial statements in the CNRC portal during all the study's periods without considering financial companies. It is worth mentioning that the CNRC requires companies to publish the balance sheet and income statement, while providing the cash flow statement is voluntary. Consequently, we excluded companies that did not publish their cash flow statement, which is necessary to estimate real earnings management. Additionally, the financial statements of all selected companies are subject to auditing since commercial law in Algeria obligates the majority of companies to appoint a financial auditor at least. Tab. 1 summarises the characteristics of the sample.

3.2 Model Specification

This study used two models by running Panel Data Regression. Model (1) studies the association of accounting earnings management as a dependent variable with the Covid-19 pandemic as an independent variable and financial leverage, company size, return on equity, and capital intensity as control variables, as shown in Equation (1):

$$\begin{aligned} \mathrm{AEM}_{it} = {} & \alpha_0 + \alpha_1\,\mathrm{COV}_{it} + \\ & + \alpha_2\,\mathrm{SIZE}_{it} + \alpha_3\,\mathrm{LEV}_{it} + \\ & + \alpha_4\,\mathrm{ROE}_{it} + \alpha_5\,\mathrm{CAP}_{it} + \\ & + \alpha_6\,\mathrm{COV} \times \mathrm{SIZE}_{it} + \\ & + \alpha_7\,\mathrm{COV} \times \mathrm{LEV}_{it} + \\ & + \alpha_8\,\mathrm{COV} \times \mathrm{ROE}_{it} + \\ & + \alpha_9\,\mathrm{COV} \times \mathrm{CAP}_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where AEM represents the accounting earning management level for the year; COV is a dummy variable, taking the value 1 for the Covid-19 period, otherwise 0; SIZE is the size of the company at the beginning of the fiscal year; LEV is the level of financial leverage at the fiscal year's end; ROE is the return on equity for the year; CAP is the capital intensity for the fiscal year; α_0 is the constant; $\alpha_1, \ldots, \alpha_9$ are the coefficients of regression; ε_{it} is the error term.

Model (2) studies the association of real earnings management as a dependent variable with the previously independent and control variables mentioned in Model (1), as shown in Equation (2):

$$\begin{aligned} \mathrm{REM}_{it} = {} & \beta_0 + \beta_1\,\mathrm{COV}_{it} + \\ & + \beta_2\,\mathrm{SIZE}_{it} + \beta_3\,\mathrm{LEV}_{it} + \\ & + \beta_4\,\mathrm{ROE}_{it} + \beta_5\,\mathrm{CAP}_{it} + \\ & + \beta_6\,\mathrm{COV} \times \mathrm{SIZE}_{it} + \\ & + \beta_7\,\mathrm{COV} \times \mathrm{LEV}_{it} + \\ & + \beta_8\,\mathrm{COV} \times \mathrm{ROE}_{it} + \\ & + \beta_9\,\mathrm{COV} \times \mathrm{CAP}_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where REM represents the real earning management level for the year; β_0 is a constant; $\beta_1, \ldots, \beta_9$ are the coefficients of regression; ε_{it} is the error term.

Tab. 1: Sample characteristics

Property		**Listing**		**Sector**	
State	82	Listed	4	Manufacturing	37
Non-state	68	Unlisted	146	Services	35
				Construction	31
				Transportation	24
				Infrastructure	15
				Energy	8
Total	150	Total	150	Total	150

3.3 Measuring the Variables

3.3.1 Accounting Earnings Management (AEM)

AEM was measured using discretionary accounting accruals, following the model of Kothari et al. (2005):

$$\frac{\mathrm{ACC}_{it}}{\mathrm{As}_{it-1}} = \lambda_0 + \lambda_1 \left(\frac{1}{\mathrm{As}_{it-1}}\right) + \\ + \lambda_2 \left(\frac{\Delta\mathrm{SL}_{it} - \Delta\mathrm{RC}_{it}}{\mathrm{As}_{it-1}}\right) + \\ + \lambda_3 \left(\frac{\mathrm{PPE}_{it}}{\mathrm{As}_{it-1}}\right) + \\ + \lambda_4 \,\mathrm{ROA}_{it} + \varepsilon_{it}, \tag{3}$$

where ACC_{it} is the total accruals for the fiscal year; As_{it-1} is the total assets at the opening of the fiscal year; $\Delta\mathrm{SL}_{it}$ is the variation of sales for the fiscal year; $\Delta\mathrm{RC}_{it}$ is the variation of receivables for the fiscal year; PPE_{it} is the gross property, plant, and equipment at the fiscal year end; λ_0 is a constant; $\lambda_1, \ldots, \lambda_4$ are the coefficients of regression; ε_{it} is the error term and an estimate of discretionary (abnormal) accruals.

In this paper, following previous studies, the estimated discretionary accruals as an absolute value were employed to measure accounting earnings management practices. The total accounting accruals were calculated using Equation (4):

$$\mathrm{ACC}_{it} = \Delta\mathrm{WCR}_{it} + \mathrm{NCI}_{it} - \\ - \mathrm{DOT}_{it} - \mathrm{NCE}_{it}, \tag{4}$$

where WCR is the working capital requirements for the year; NCI is the non-cash revenues for the year; DOT_{it} is the depreciation, amortisation, and impairment charges for the year; and NCE_{it} is the other non-cash expenditures for the year.

3.3.2 Real Earnings Management (REM)

Roychowdhury (2006) suggests that sales manipulation and overproduction create abnormally low operating cash flows, while the reduction of discretionary expenses creates abnormally high operating cash flows. For that, abnormal operating cash flows were employed to measure REM, which expressed as the standardised residuals of Roychowdhury's (2006) model:

$$\frac{\mathrm{OCF}_{it}}{\mathrm{As}_{it-1}} = \delta_0 + \delta_1 \frac{1}{\mathrm{As}_{it-1}} + \\ + \delta_2 \frac{\mathrm{SL}_{it}}{\mathrm{As}_{it-1}} + \\ + \delta_3 \frac{\Delta\mathrm{SL}_{it}}{\mathrm{As}_{it-1}} + \varepsilon_{it}, \tag{5}$$

where OFC_{it} represents the operating cash flows during the fiscal year; δ_0 is the constant; $\delta_1, \ldots, \delta_3$ are the coefficients of regression; ε_{it} is the residuals.

As they are unpredictable through ordinary operations, the standardised residuals of Equation (5) represent the level of real earnings management.

3.3.3 Independent Variable

The Covid-19 period (COV) was measured as a dichotomous variable, taking a value of 0 for the pre-Covid-19 period (2018–2019) and a value of 1 for the Covid-19 period (2020–2021).

3.3.4 Control Variables

The control variables were measured as follows: company size (SIZE) is the logarithm of total assets; financial leverage (LEV) is the ratio of total debt to total assets; return on equity (ROE) is the net income to total equity ratio; and capital intensity (CAP) is the ratio of average total assets to sales.

4 RESULTS AND DISCUSSION

Before presenting the results, it is worth mentioning that all study models were estimated using the method of Panel Estimated Generalised Least Squares (Panel EGLS) through EViews software (cross-section weights) due to the absence of homoscedasticity. When choosing

cross-section weights, EViews will provide a feasible GLS estimation, assuming the presence of cross-section heteroscedasticity. According to Bai et al. (2021), the FGLS is more efficient than the ordinary least squares (OLS) in the case of heteroscedasticity or serial and cross-sectional correlations. They stated that the FGLS can enhance efficiency in terms of mean squared error, providing an unbiased standard error estimator.

4.1 Accounting Earnings Management Results

Tab. 2 summarises the estimation results for Kothari et al.'s (2005) model to measure accounting earnings management (AEM) over three different periods: the pre-Covid-19 period (2018–2019), the Covid-19 period (2020–2021), and the whole study period (2018–2021). The results suggest that the model is significant at 1% for the three cases, with variation in the significance levels of the regression coefficients over the three periods. The model has high explanatory power during the Covid-19 period when compared to the other two periods with significant regression coefficients at the 1% level, except for the $\mathrm{PPE}_{it}/\mathrm{As}_{it-1}$ parameter, which is significant at 5% level, and the parameter of $(\Delta\mathrm{SL}_{it}–\Delta\mathrm{RC}_{it})/\mathrm{As}_{it-1}$, which is insignificant.

In addition, the model's explanatory power is relatively lower during the whole period compared to the Covid-19 period, although most of the regression coefficients were significant at 1%, except for the parameters of $\mathrm{PPE}_{it}/\mathrm{As}_{it-1}$ and $1/\mathrm{As}_{it-1}$, which are insignificant and significant at 5%, respectively. For pre-Covid-19, the explanatory power of was low, with insignificant regression coefficients, except for the parameters of $(\Delta\mathrm{SL}_{it}–\Delta\mathrm{RC}_{it})/\mathrm{As}_{it-1}$ and $\mathrm{PPE}_{it}/\mathrm{As}_{it-1}$, which are statistically significant at 1%.

The variables show a disparity between before and during the pandemic periods regarding their ability to explain accounting accruals. Except for the variable $(\Delta\mathrm{SL}_{it}–\Delta\mathrm{RC}_{it})/\mathrm{As}_{it-1}$, all the variables explain a part of accounting accruals during the Covid-19 period, while only the variables $(\Delta\mathrm{SL}_{it}–\Delta\mathrm{RC}_{it})/\mathrm{As}_{it-1}$ and $\mathrm{PPE}_{it}/\mathrm{As}_{it-1}$ explain accounting accruals during the pre-pandemic period. We note that the coefficient of determination (R^2) has increased in the pandemic period compared to the pre-pandemic period, which implies that the standardised residuals as a measure of accounting earnings management have decreased. Consequently, Covid-19 has negatively influenced accounting earnings management.

4.2 Real Earnings Management Results

The estimation results of real earnings management (REM) using Roychowdhury's (2006) model during the same previous three periods summarised in Tab. 3 indicate that the model is significant at 1%. The significance levels

Tab. 2: The estimation results for Kothari et al.'s (2005) model

	Pre-Covid-19		Covid-19		Whole period	
Variables	**Coeffi.**	***t*-Stati.**	**Coeffi.**	***t*-Stati.**	**Coeffi.**	***t*-Stati.**
Constant	−0.002	−0.550	−0.055	−11.36*	−0.030	−7.14**
$1/\mathrm{As}_{it-1}$	−167511	−1.27	695736	5.68**	312778	2.05*
$(\Delta\mathrm{SL}_{t}–\Delta\mathrm{RC}_{t})/\mathrm{As}_{t-1}$	−0.005	−12.16**	−0.009	−1.76	−0.014	−4.76**
$\mathrm{PPE}_{t}/\mathrm{As}_{t-1}$	−0.064	−8.50**	0.040	2.48*	−0.010	−0.572
ROA_{t}	−0.008	−0.104	0.534	24.27**	0.414	10.3**
F-Stati.	15.38**		37.43**		26.27**	
Adj. R^2	0.173		0.337		0.150	
Durbin-Watson	2.17		2.12		2.07	

Notes: Dependent variable: $\mathrm{ACC}_{it}/\mathrm{As}_{it-1}$. Estimation method: Panel EGLS (Cross-section weights). Significant at 0.05 (*) or 0.01 (**) level.

Tab. 3: The estimation results for Roychowdhury's (2006) model

Variables	Pre-Covid-19		Covid-19		Whole period	
	Coeffi.	*t*-Stati.	Coeffi.	*t*-Stati.	Coeffi.	*t*-Stati.
Constant	0.019	38.69**	0.057	18.04**	0.043	7.94**
$1/\mathrm{As}_{it-1}$	−318324	−1.59	−703642	−9.13**	−575868	−3.24**
$\mathrm{SL}_{it}/\mathrm{As}_{it-1}$	0.063	7.99**	0.009	1.22	0.017	6.54**
$\Delta\mathrm{SL}_{it}/\mathrm{As}_{it-1}$	−0.029	−3.94**	0.017	5.46**	0.016	8.25**
F-Stati.	23.29**		16.53**		18.10**	
Adj. R^2	0.191		0.144		0.084	
Durbin-Watson	2.09		1.98		2.06	

Notes: Dependent variable: $\mathrm{OCF}_{it}/\mathrm{As}_{it-1}$. Estimation method: Panel EGLS (Cross-section weights). Significant at 0.05 (*) or 0.01 (**) level.

of the regression coefficients are similar over the three periods, which are significant at 1%, except for the parameter of $1/\mathrm{As}_{it-1}$ during the pre-Covid-19 period and the parameter of $\mathrm{SL}_{it}/\mathrm{As}_{it-1}$ during the Covid-19 period that are insignificant. The signs of the regression coefficients are also homogeneous over the periods, except for the parameter of $\Delta\mathrm{SL}_{it}/\mathrm{As}_{it-1}$; while there is a disparity between the three periods regarding the values of the regression coefficients.

The model presents different levels of explanatory power over the periods, which decreased during Covid-19 compared to pre-Covid-19 and was relatively lower during the whole period. This is due to the disparity between periods in terms of variables' ability to explain operating cash flows. The decline in the model's explanatory power, as reflected by the decrease in the determination coefficient during the pandemic compared to before, means that standardised residuals as a measure of real earnings management have increased, suggesting an increase in real earnings management during the Covid-19 period.

4.3 Descriptive Statistics

Tab. 4 presents the descriptive statistics for variables. The mean of accounting earnings management, measured by the absolute value of discretionary accruals, shows that Algerian companies used discretionary accruals to manage earnings with 12.90% of total assets, on average, over the study period. However, the mean of real earnings management (abnormal operating cash flows) shows that Algerian companies used sales and operating activities to manage earnings with 2% of total assets, on average, over the study period.

Tab. 4: Data descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
AEM	0.056	1.872	0.001	0.213	0.129	600
REM	0.020	−0.025	2.015	−1.691	0.275	600
COV	–	–	1	0	–	600
SIZE	8.950	9.006	11.677	6.106	1.047	600
LEV	0.605	0.496	8.047	0.000	0.691	600
ROE	0.087	0.061	4.565	−20.591	0.987	600
CAP	4.427	0.239	0.691	0.000	0.364	600
COV × SIZE	8.874	6.669	11.677	0.000	4.498	600
COV × LEV	0.521	0.000	3.889	0.000	0.510	600
COV × ROE	0.061	0.000	4.379	−0.994	0.367	600
COV × CAP	5.387	0.000	0.691	0.000	0.247	600

Tab. 5: The results of unit root test

	LLC *t*	Fisher Chi-square – PP	Fisher Chi-square – ADF
AEM	−112.77**	697.05**	597.92**
REM	−48.33**	815.83**	679.82**
COV	−7.30**	521.65**	97.33
SIZE	−28.08**	581.54**	495.84**
LEV	−26.39**	665.27**	593.26**
ROE	−4131.22**	776.94**	692.78**
CAP	−58.18**	513.76**	606.80**
COV × SIZE	−7.31**	532.19**	100.94
COV × LEV	0.89	312.12**	327.19*
COV × ROE	−129.15**	680.49**	108.46**
COV × CAP	−28.32**	513.45**	224.34**

Notes: Null hypothesis: Unit root. Lags: Automatic selection of maximum lags.
Significant at 0.05 (*) or 0.01 (**) level.

In addition, the mean of the capital intensity indicates that producing one DZD as sales requires Algerian companies to provide 4.427 DZD as total assets, on average, which increased to 5.387 DZD during the Covid-19 period. The mean of the leverage ratio suggests that the total debt of Algerian companies represented, on average, 60.50% of total assets during the study period, more than that recorded during the Covid-19 period (52.10%). Similarly, the mean of the return on equity ratio shows that Algerian companies earned 8.7% on average during the study period, more than what they earned during the Covid-19 period (6.10%). This drop in leverage and performance of Algerian companies during the Covid-19 period can be attributed to the economic downturn imposed by the closure and physical distancing, leading to a financial and liquidity crisis that limited the financing sources available for companies. Finally, by comparing the standard deviation with the range of each variable, it appears that the dispersion of the variables is adequate.

4.4 Unit Root Test

Before estimating Models (1) and (2), it is necessary to test the stationarity of the data to determine which statistical method is appropriate for estimating the models. As shown in Tab. 5, the stationarity test was based on three tests: the Phillips-Perron (PP) test, the Augmented Dickey-Fuller (ADF) test, and the Levin-Lin-Chu (LLC) test. According to the results, all variables are stable at the level, except for the variable COV × LEV (when using the LLC test) and the variables COV and COV × SIZE (when using the ADF test), which are insignificant at the level of 5%. Therefore, all variables do not contain unit roots, and thus the estimation of Models (1) and (2) does not require using dynamic methods.

4.5 Model (1)'s Results

Tab. 6 summarises the estimation outcomes of Model (1), which assesses the effect of the pandemic on accounting earnings management (AEM). The findings indicate that the model is significant at 1%, and the adjusted R^2 reached 0.36, which means that the independent variables collectively explain 36% of the variance in the dependent variable (AEM). For model validity, the Jarque-Bera statistic is insignificant and suggests that the residuals of Model (1) have a normal distribution. The Durbin-Watson statistic that reached 2.12 is close to 2, which means that the residuals of Model (1) are not autocorrelated. Finally, the variance inflation factors (VIF) are weak, indicating the absence of collinearity between independent variables.

Tab. 6: The estimation results of Model (1)

Variables	Coeffi.	*t*-Stati.	VIF	*F*-Stati.	Adj. R^2	Durbin-Watson	Jarque-Bera
Constant	0.041	1.38		3.12**	0.36	2.12	5.31
COV	−0.246	−4.38**	2.13				
SIZE	−0.007	−2.26*	2.11				
LEV	−0.003	−0.39	1.59				
ROE	0.013	4.15**	1.17				
CAP	−0.031	−2.49*	1.50				
COV × SIZE	0.030	5.24**	2.14				
COV × LEV	−0.044	−4.11**	1.89				
COV × ROE	−0.033	−2.07*	1.27				
COV × CAP	0.029	1.35	1.65				

Notes: Dependent variable: AEM. Estimation method: Panel EGLS (Cross-section weights).
Significant at 0.05 (*) or 0.01 (**) level.

The results of the coefficients show a negative influence of Covid-19 (COV) on accounting earnings management, as the parameter reached −0.246 and is significant at 1%, which means that during the pandemic, accounting earnings management levels declined compared to before. The results also show that all parameters of control variables are significant at 1%, except for SIZE, CAP, and COV × ROE, which are considered significant at 5%, and LEV and COV × CAP, which are considered insignificant. Additionally, company size (SIZE) and capital intensity (CAP) negatively affect accounting earnings management. However, these effects turn positive for company size (COV × SIZE) and insignificant for capital intensity (COV × CAP) during the Covid-19 period. Contrarily, the results show that return on equity (ROE) positively affects accounting earnings management, but this effect becomes negative (COV × ROE) during Covid-19. Furthermore, the insignificant effect of leverage (LEV) on accounting earnings management becomes negative (COV × LEV) during Covid-19.

4.6 Model (2)'s Results

Tab. 7 summarises the estimation outcomes of Model (2), which assesses the influence of the Coronavirus period on real earnings management. The findings show that the model is significant at 1%, and the adjusted R^2 reached 0.29, which means that the independent variables collectively explain 29% of the variance in the dependent variable (REM). Regarding model validity, the Jarque-Bera statistic is insignificant, suggesting the normal distribution of the residuals of Model (2). The Durbin-Watson statistic reached 2.09 and is close to 2, which demonstrates the non-autocorrelation of the residuals of Model (2). Finally, the results suggest the absence of collinearity between the independent variables in Model (2) since the variance inflation factors (VIF) are weak.

The results suggest that the pandemic (COV) has a positive impact on real earnings management, as the value of the parameter reached 0.093 and is significant at 1%, meaning that real earnings management levels were higher in the Covid-19 period than they existed before the Covid-19 period. The results also show that all parameters of control variables are significant at 1%, except for LEV, CAP, and COV × SIZE, which are significant at 5%, and COV × CAP, which is insignificant. Furthermore, the results indicate that company size (SIZE) and leverage (LEV) positively affect real earnings management, while these effects become negative (COV × SIZE and COV × LEV) when interacting with the Covid-19 pandemic. However, the negative influence of return on equity (ROE) becomes positive (COV × ROE) during the Covid-19 period, and the positive effect of capital intensity (CAP) becomes insignificant (COV × CAP) during the Covid-19 period.

Tab. 7: The estimation results of Model (2)

Variables	Coeffi.	*t*-Stati.	VIF	*F*-Stati.	Adj. R^2	Durbin-Watson	Jarque-Bera
Constant	−0.206	−7.15**		2.52**	0.29	2.09	3.96
COV	0.093	3.11**	2.13				
SIZE	0.014	4.89**	2.11				
LEV	0.008	2.03*	1.59				
ROE	−0.005	−5.50**	1.17				
CAP	0.009	2.18*	1.50				
COV × SIZE	−0.008	−2.55*	2.14				
COV × LEV	−0.013	−2.97**	1.89				
COV × ROE	0.015	3.18**	1.27				
COV × CAP	−0.003	−0.46	1.65				

Notes: Dependent variable: REM. Estimation method: Panel EGLS (Cross-section weights).
Significant at 0.05 (*) or 0.01 (**) level.

4.7 Discussion

The findings of this study suggest that the pandemic has restricted accounting earnings management in Algerian companies, which refutes hypothesis 1. This result confirms the findings of Rusmianto and Makhsun (2021), who found a significant decrease in accounting earnings management behaviour during the Covid-19 period. However, this result differs from previous studies showing no significant difference in the levels of accounting earnings management between the pre- and Covid-19 periods (e.g., Jordan et al., 2021; Ardiany et al., 2022; Azizah et al., 2022). It also differs from the results of several studies that revealed an increase in accounting earnings management due to the Covid-19 (e.g., Usheva and Vagner, 2020; Dicken and Unger, 2021; Aljawaheri et al., 2021; Lassoued and Khanchel, 2021; Flores et al., 2021; Taylor et al., 2023).

Additionally, the findings of this study indicate that the pandemic has intensified real earnings management in Algerian companies, which confirms hypothesis 2. This result is in harmony with some studies showing that companies practised more real earnings management during the Covid-19 period (e.g., Yassin et al., 2022; Hsu and Yang, 2022; Yan et al., 2022). On the contrary, this result is inconsistent with the study of Ljubisavljević and Jakobsson (2022), which showed that real earnings management levels have not changed due to the pandemic, as well as with the study of Xiao and Xi (2021), which reported a significant decrease in the levels of real earnings management during the Covid-19 period.

Tab. 8 summarises a categorisation of the results of previous studies territory, development level, and their consistency with the present study.

Although the cost of real earnings management is higher than that of accounting earnings management, the Coronavirus has forced the managers of Algerian companies to turn towards real earnings management since it is considered more difficult to discover and subject to less oversight by external auditors and regulators than accounting earnings management. Real earnings management also directly affects cash flows, which enabled companies to reduce the severity of liquidity problems imposed by the pandemic due to business restrictions. Thus, Algerian companies can simultaneously enhance their financial performance and their liquidity situation. Moreover, to deal with the low level of activity caused by the pandemic, managers of Algerian companies did not find many accounting choices to manipulate earnings, so they resorted to real earnings management to provide more alternatives.

Tab. 8: Categorisation of the results by territory and development level

Criterion	Categories	Studies
Consistent studies with the present study		
Territory	Southeast Asia	Rusmianto and Makhsun (2021), Yan et al. (2022), Ryu and Chae (2022)
	USA	Yassin et al. (2022)
	Europe	Hsu and Yang (2022)
	MENA	Yassin et al. (2022)
Development level	Developing	Yassin et al. (2022)
	Emerging	Rusmianto and Makhsun (2021), Yan et al. (2022), Ryu and Chae (2022)
	Developed	Hsu and Yang (2022), Yassin et al. (2022)
Inconsistent studies with the present study		
Territory	Southeast Asia	Xiao and Xi (2021), Azizah et al. (2022), Ardiany et al. (2022), Hariadi and Kristanto (2022)
	USA	Jordan et al. (2021), Flores et al. (2021)
	Europe	Usheva and Vagner (2020), Dicken and Unger (2021), Lassoued and Khanchel (2021), Taylor et al. (2023), Ljubisavljević and Jakobsson (2022)
	MENA	Aljawaheri et al. (2021)
Development level	Developing	Aljawaheri et al. (2021)
	Emerging	Usheva and Vagner (2020), Flores et al. (2021), Xiao and Xi (2021), Hariadi and Kristanto (2022), Azizah et al. (2022), Ardiany et al. (2022)
	Developed	Jordan et al. (2021), Dicken and Unger (2021), Lassoued and Khanchel (2021), Flores et al. (2021), Ljubisavljević and Jakobsson (2022), Taylor et al. (2023)

5 CONCLUSION

Several studies have argued that periods of economic distress prompt managers to change their tendencies towards earnings management. However, few studies have explored this trend regarding two different earnings management strategies. Therefore, this study analyses the influence of Covid-19 on real and accounting earnings management in Algerian companies. The results indicate that Algerian companies use real and accounting earnings management as substitutes. This finding was consistent with the study by Kimouche (2022). Moreover, with the outbreak of the Covid-19 pandemic, Algerian companies have changed from accounting earnings management to real earnings management. Thus, Covid-19 restricted accounting earnings management while intensifying real earnings management in Algeria.

These results can be attributed to the Covid-19 pandemic nature, which has directly influenced the real economy through restrictions on companies' activity due to preventive measures against the pandemic outbreak. On the contrary, the financial crises that occurred during the previous decades have indirectly affected the real activity of companies. Restricting the companies' activity reduces the margin of discretion available to managers regarding accruals, leading them to turn to cash flows as a means to manipulate earnings. This strategy enables managers to mitigate losses arising from underperformance and, at the same time, manage liquidity risks, both of which are consequences of the pandemic. In addition, managers have the opportunity to avoid the vigilance of auditors and regulators regarding accounting earnings management.

The study contributes to accounting research by exploring earnings management during the Covid-19 period, which has directly and globally influenced the performance of companies and their financial position through the restrictions imposed on their activity to limit the pandemic's spread. Moreover, this study is the first

in Algeria, which has very different economic and institutional characteristics compared to other environments and experienced different conditions during the pandemic with different government measures to reduce the pandemic's consequences. Methodologically, this study included two years during the pre-Covid-19 period versus two years during the Covid-19 period and measured the impact of the pandemic on earnings management behaviour based on a multiple regression model (Panel EGLS). Contrarily, the majority of previous studies have only covered 2020 as the Covid-19 period, compared to many years for the pre-Covid-19 period, and relied on the paired difference tests.

The results of the study have many implications, as they require accounting standard-setters and regulators to give more attention to the influences of crises on companies' financial situations and the quality of financial reporting. During crisis periods, accounting discretion should be constrained by more disclosure requirements and the identification of aspects that require disclosure. On the other hand, auditors should be encouraged to enhance their analytical procedures and improve audit quality during times of crisis in order to detect material misstatements in financial statements resulting from earnings manipulation. Finally, users of financial reporting should be careful when using financial information in times of crisis.

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