FACTORS AFFECTING THE FREQUENCY OF ONLINE SHOPPING OF YOUNG CONSUMERS IN THE POST-COVID-19 ERA

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Received: December, 2022
1st Revision: March, 2023
Accepted: June, 2023

ABSTRACT
Background: Understanding of drivers of online shopping is crucial in today's digitized world. The COVID-19 pandemic highly influenced young consumers shopping behavior and rapidly raised their preference for online shopping. **Aims:** The aim of this paper was to investigate which factors affect the frequency of young consumers' online shopping in the post-pandemic era. **Methods:** The data were evaluated by application of the Generalized linear model. **Sample:** The primary data were collected through a self-administered questionnaire with 635 respondents. Results: The results showed that the perceived e-trust and the usage of social media (expressed through factors such as frequency of use and promotion on social media) influence the frequency of online shopping of these consumers. The research also revealed that males tend to shop online more than females. **Conclusions:** Social media usage, e-trust and promotion on social media proved as significant factors affecting the frequency of online shopping of young consumers. The factor of gender showed up significant too. **Implications:** It is important to differentiate the contents of the messages on social media based on gender and the customer segments to whom the communication and promotions on social media are addressed.

Keywords: online shopping; e-commerce; frequency of online shopping; young consumers; consumer behavior

***JEL Classification**:* M31; M37; M39

DOI: 10.54933/jmbrp-2023-15-1-1

Pencarelli, T., Skerhakova, V. & Tirpak, D. (2022). Which factors affect the frequency of online shopping of young consumers in the post-pandemic era?. Journal of Management and Business: Research and Practice, 15(1). doi: 10.54933/jmbrp-2023-15-1-1

Introduction

The development of Web 2.0 and the technical innovations in the field of communication have increasingly focused on the social aspect of online users in recent years. This change of perspective has transformed the Internet user from a passive recipient of information to an active co-creator of web content (Verhoef et al., 2019). This type of interactivity gives users numerous opportunities to participate in social media. Writing, distributing and commenting on information is now part of our everyday life. This progress in communication technologies, digital networking through social media and the resulting interactive communication between market participants have brought about significant changes in online retail. The covid-19 pandemic has posed a threat to several human lives as well as numerous global developments. However, it turned into the biggest chance for e-commerce. People were left in public spaces, and every country went into lockdown. Daily essentials remained constant in the interim. Due to this hazard, online shopping has allowed everyone to conveniently buy their essentials while also saving their lives. In order to bring the terms social media and online purchasing behavior together (Bai et al., 2015). It was necessary to address the changes in online trade caused by the development of social media, which can be used to mediate or reinforce change in customer online shopping behaviour. Overall, longer-term and higher-quality studies should be conducted. According to Al-Adwan (2018), the supplier's encouragement of customers' positive attitudes towards online shopping has increased their intent to make purchases. Therefore, in order to do this, it is essential to increase consumer confidence and sense of security and reduce perceived risks during purchase and sale transactions by guaranteeing information confidentiality and individual privacy when users use the website and the provider's reputation. Social commerce stands for a form of e-commerce in which consumers are involved in the marketing process. While the relationships between companies and customers are unidirectional in classic e-commerce, social commerce redefines this type of interaction and the classic allocation of roles.

In the issue of shopping online, trust is a ubiquitous, complex and multifaceted phenomenon, and for this reason, trust plays an important role in consumer purchasing behaviour. The goal is to understand and explain the purchasing behavior of consumers in order to derive recommendations for action to influence consumption specifically.(Alzaidi et al., 2020). E-trust was a key aspect, according to many earlier academics, in the impact of consumer purchase intent. It is specifically classified into a number of categories that correlate to the various parts of the online goods sale industry (Tran et al., 2022).

According to Jain et al. (2021) various digital payment methods are used both at the point of sale and for online shopping on commercial trading platforms or as part of C2C goods trading. What the different technologies have in common is that payment processes are drastically accelerated and simplified, which on the one hand, means that goods are available to the consumer more quickly, and on the other hand, the transaction costs for the consumer are reduced. Digital payment has long been widespread using, e.g. giro cards, credit cards or electronic transfers. In addition, however, other forms of digitized payment are constantly being developed, in particular those of mobile payment. In this context, the issue of security and awareness of risks in online payments comes into play.

Sago (2015) stated that the payment process for online purchases is increasingly being handled by payment service providers, which close the time gap between sending and receiving an amount of money that occurs when transferring money through traditional financial institutions. In rare cases, the service providers themselves have a banking license (e.g. PayPal). Convenience is often more important than caution. Organizations should remain vigilant and ensure that cybersecurity strategy is aligned with new consumer behaviors for the year ahead.

Whether the covid-19 pandemic, environmental awareness or the desire to support local trade - a wide variety of factors are influencing the frequency of online shopping in the post-pandemic era. Facebook and Instagram have been steadily expanding their shopping functions for several years, and WhatsApp and Twitter have recently followed suit. For a long time, users have been buying not only from online shops but also where they spend a lot of time anyway: on social networks. Whether individual products or entire collections, due to the advanced algorithm, buyers become aware of such products. People have different perspectives on how the internet is used for buying and selling. Some people consider it to be a better choice than in-person shopping because of its practicality. Brick and mortar shops have difficulty having an impact since they cannot reach the entire country. On the other hand, internet shopping and merchants make their product portfolio available to a variety of people throughout the world, making goods that would otherwise be difficult to obtain accessible (Aseri, 2021). As stated above, many factors have an impact on online shopping, but the question is if all these factors should have an impact also on the frequency of online shopping of young consumers in the post-pandemic era.

Methods

The aim of this paper was to investigate which factors influence the frequency of young consumers‘ online shopping in the post-pandemic era. The research was focused on the investigation of two socio-demographic factors (gender and age) and five selected factors which were named according to the context of the questions: 1) Social media usage (SMU) – 6 variables; 2) Feelings (FEE) -5 variables; 3) E-commerce trust (ECT)- 10 variables; 4) Attitudes (ATT) – 9 variables and 5) Promotion on social media (PSM) – 8 variables. The variables and factors were derived from the studies of Pencarelli et al. (2018), Pencarelli et al. (2020) and Ali Taha et al. (2021). The data were obtained by a self-administered questionnaire by the online platform Google Forms, and 635 respondents participated in this survey conducted in April 2022 in the territory of the Slovak Republic. The research sample consisted of young consumers who are considered to be the representatives of the Millennial and Post-Millennial generations. Methods of descriptive statistics were applied in order to construct the latent factors from manifest variables. Subsequently, the generalized linear model (GLM) was constructed in order to explain the frequency and intensity of online shopping on the basis of behavioural (five factors) and demographic characteristics of respondents (generation and gender). Data were processed by Microsoft Excel. Modelling and creation of plots were conducted in R 3.4.4 environment for statistical computing (R Core Team 2021).

Results

The demographic characteristics of the respondents showed that 635 respondents took part in this research, where 274 were representatives of Millennials and 361 respondents belonged to the Post-Millennials generation. Regarding the gender representation of respondents, 237 men (87 Millennials and 150 Post-Millennials) and 398 women (187 Millennials and 211 Post-Millennials) participated in this research.

As the first part of this analysis, the total score points for each respondent were calculated and converted from the responses on the Likert scale (1-5) to a scale of 0 to 100%. Higher percentages always indicate a higher rate/intensity of the domain, which corresponds to the degree of agreement with statements in the questionnaire (1 - disagreement; 5 - agreement).

Table 1. Descriptive statistics of latent factors

	Mean	Std.Dev	Median	Skew.	Kurtosis	SE
Social media usage (SMU)	60.79	12.71	63.33	-0.29	0.26	0.51
Feelings (FEE)	39.64	26.61	40	0.44	-0.51	1.07
E-commerce trust (ET)	60.48	7.51	60	-0.01	0.07	0.3
Attitudes (ATT)	61.27	14	62.22	-0.8	0.98	0.56
Promotion on social media (PSM)	58.68	16.24	60	-0.45	0.15	0.65
Frequency of online shopping (FOS)	43.95	13.95	41.67	0.59	-0.31	0.56

Source: *processed by the authors (2022)*

As it is evident from these results, the factors with the highest rate are Social Media Usage (SMU), E-commerce Trust (ECT) and Attitudes (FEE). The factor with the lowest rate represents factor Feelings, where the respondents evaluated their concerns about in-person shopping in re-opening the physical stores. However, the concerns of respondents were lower than we expected. The highest rate recorded factor Attitudes, where the attitudes of respondents in shopping online were evaluated. The social media usage factor showed the frequency of use by our respondents. Factor “frequency of online shopping” was constructed by 6 variables and entered into the model as a dependent variable.

The initial model was compiled as the most complex possible (i.e. full models), and their terms were subsequently tested by analysis of deviance. In the next step, we simplified them by step-by-step removal of their insignificant terms while respecting the rule of marginality (i.e. it is not possible to remove an insignificant term which is part of a significant higher-order interaction) - this further irreducible (minimal adequate) model is presented in the form of a diagnostic table (Table 1.) Based on values of null and residual deviance, we calculated pseudo-R2, which captures the proportion of the variation in the dependent variable that is predictable from a set of independent variables. The model was visualized by lines with 95% confidence intervals derived from fitted values ±1.96×SE on the link scale, whereas the link function was used to map the fitted values and the upper and lower limits of the interval back onto the response scale.

Table 2. Minimal adequate GLM model

	Estimate	Std. Error	t-value	p-value
(Intercept)	6.432	5.121	1.256	0.209
Gender [male]	4.908	1.297	3.782	< 0.001 ***
SMU	0.103	0.047	2.176	0.029 **
E-trust	0.227	0.085	2.663	0.007 **
PSM	0.276	0.038	7.197	< 0.001 ***
Null deviance=171481; Residual deviance=138280; *pseudo*-R^2 = 19.36%				

Source: *processed by the authors (2022)*

The resulting model indicates four significant factors influencing online shopping frequency among Millennials and Post-Millennials. The results of the model showed that age does not play a significant role in understanding what influences the frequency of online shopping. Based on the tests applied to our dataset, we can conclude that no statistically significant differences in the frequency of online shopping were detected between the analysed generations of Millennials and Post-Millennials. On the other hand, results underlined the importance of gender in this issue. The testing revealed statistically significant differences between the genders, while men shop online more often than women. From Figure 1, we can observe that social media usage positively influences the frequency of online shopping of males. From this figure is also evident that in the case of males, the frequency of online shopping is also positively connected with promotion on social media as with e-commerce trust.

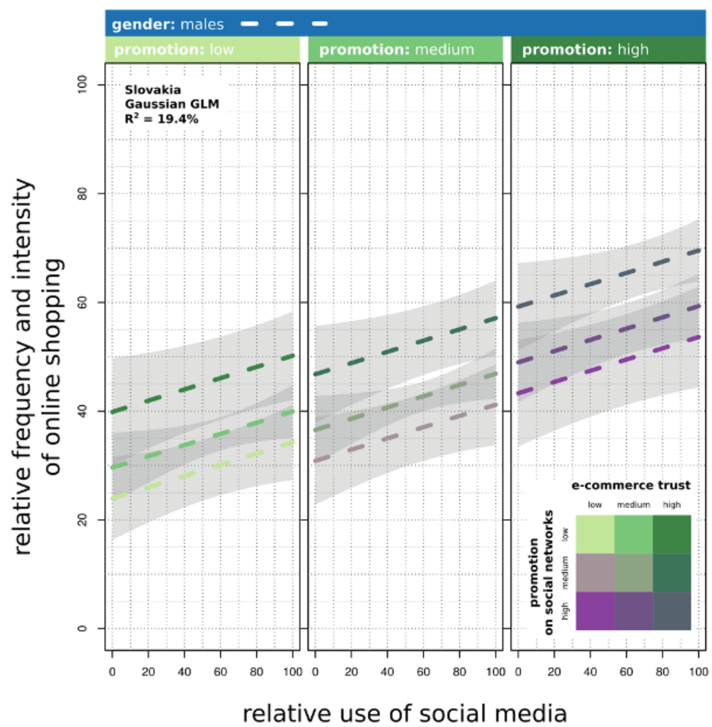

Figure 1. Visualization of generalized linear model separately for males.

Source: processed by the authors (2022)

In addition to gender, three of the five domains (SMU, ECT and PSS) were confirmed as significant. However, it is a consistent pattern that all significant domains positively affect the frequency of online shopping. The results of the GLM model confirmed that consumers are more likely to buy online products which have bigger promotions on social media (the bigger the campaign, the better the sales). Based on our results, we can also conclude that consumers who are active on social media do online shopping significantly more often, what means that the more time these consumers spend on Facebook or Instagram, the more they tend to buy online. It is probably caused by social media advertising campaigns. Another result of our analysis showed that the consumers who do online shopping most often are those who have a high level of trust in digital security, which they probably gained through repeated purchases. The descriptive GLM model is quite strong - we can explain about 20% of the variability of respondents' online shopping based on the factors mentioned above. Factors Attitude, Feelings and "generation" did not contribute to explaining the frequency of online shopping behavior.

Discussion and conclusion

Stefko et al. (2015) highlighted the importance of web pages, which, according to their research, are considered the main tool of e-marketing in terms of communication. According to the results of our research, we can conclude that communication with loyal and potential young consumers on social media is also important because of two factors – their time spent on social media and their perception of the promotion of the product on social media. The reason for this is the new forms of communication between merchants and their target customers and also the fact that only one customer review can influence a broad mass of potential customers (Stefko et al., 2016). It is very difficult to succeed in the field of brands and merchants battles on social media because of overwhelming amount of their content and competition (Nastisin et al., 2019).

The results of Sulastini's et al. (2018) and Bacik et al. (2020) researches indicate that gender doesn't play a significant role in terms of online shopping but our results proved the opposite. Also, the study of Boustani et al. (2022) aimed on the attitudes towards online shopping during the pandemic times proved that important aspect of consumers' attitudes toward online shopping is gender, which represents a major parameter in purchasing products online and that the types of goods differ according to whether the customer is male or female. The study of Shukla et al. (2021), highlights that perceived benefit, website aesthetics, and Internet self-efficacy positively and significantly impact working women's purchase intention and confirms there are differences between genders in the issue of online shopping. The Birknerova et al. (2018) research even proved there are significant differences in advertising perception between men and women. According to the results of the same research, there is a significant relationship between the credibility of the merchants' website and its presentation on social media what was confirmed also by our results (Sulastini et al., 2018). We can conclude that the factor of a gender plays significant role in the frequency of online shopping within young consumers. According to our results, the statistical significant differences between generation Y and Z wasn't proved.

Online store managers must also differentiate marketing actions based on the type of products on sale (convenience, shopping or specialty goods) for which the perceived risk in purchases is different. It is probable that the perception of risk in purchases differs between men and women. Further managerial challenges are linked to the channel strategies adopted by the sellers: if omnichannel strategies are adopted, it is necessary to take into account the fact that women love to spend their time shopping at physical points of sale to better and more accurately observe the quality of the products and to enter into personal relationships with the sales staff. It is also important to take into consideration the fact that young women prefer the social e-shopping site to traditional e-shopping (Dennis et al. 2010).

From the perspective of the results of this study, there are some managerial implications for managers. The e-merchants should pay attention to the quality of online communication on social media, as this factor proved to be significant in the issue of frequency of online shopping. It is also important to transfer the young consumers to the e-merchant's profile on social media because it could help to engage the consumers through targeted communication. They should try to differentiate the contents of the messages on the basis of the gender of the customer segments to which the value propositions are addressed. The content on social media is overwhelming so the promotion on social media is directly linked to the previous implications. Without promotion of the e-merchant's content should, their communication to the consumer disappears in a large amount of other content on social media.

As with every research, also this has its limitations like the origin of the respondents only from the Slovak Republic or affiliation of the respondents only to young generations (Millennials and Post-Millennials). The future orientation in the field of this problematics should focus on investigating the factors affecting the frequency of online shopping of older generations like Generation X. Due to the lack of knowledge in the field of this problematics, it is also important to investigate which factors influence women and men in online shopping in order to find content marketing solutions and suitable communication and social channels.

Acknowledgements

This article is one of the partial outputs under the scientific research grants GAPU 15 /21 and VEGA 1/0694/20 – Relational marketing research - perception of e-commerce aspects and its impact on purchasing behavior and consumer preferences.

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JOURNAL OF MANAGEMENT AND BUSINESS: RESEARCH AND PRACTICE
2023 15(1) ISSN 1339-9381

BIG DATA AND EXCHANGE RATE EFFICIENCY IN NIGERIA: ANY ROLE FOR INVESTMENT SENTIMENTS?

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Received: January, 2023
1st Revision: February, 2022
Accepted: March, 2023

ABSTRACT. The efficiency of the exchange rate is a strong indicator to determine appropriate exchange rate returns. This study engages the use of big data to investigate exchange rate efficiency in Nigeria and further examine the role of investment sentiments. The study employs both the unit-root and variance ratio tests. Also, the granger causality test was employed to investigate the direction of causality. The data spanned 4,992 daily observations each for exchange rate and investment sentiments and cover the daily period 12/10/2001 – 5/13/2022. For further interrogation, quarterly and yearly data frequencies of these two variables were employed in order to explain the varieties of big data. With recourse to the effect of big data, results show that the exchange rate exhibits a random walk behaviour in Nigeria only for daily and quarterly data frequencies and not for the yearly data frequency. However, the causality test indicates that investors' speculations do not affect exchange rate dynamics in the country. As the exchange rate is found efficient in Nigeria, the monetary authority is enjoined to promote real-time information about the exchange rate to deflect undue speculations by investors. This study implies that the monetary authority in Nigeria should model exchange rate efficiency around its intrinsic data-generating process.

Keywords: Big data, Exchange rate, Efficiency, Investment sentiments, Random walk, Unit root test, Granger causality, Real-time.

JEL Classification: **C38, C55, F31, G14, G11**

DOI: 10.54933/jmbrp-2023-15-1-2

Ayinde, T. O., & Adeyemi, F. A. (2023). Big Data and Exchange Rate Efficiency in Nigeria: Any Role for Investment Sentiments? Journal of Management and Business: Research and Practice, 15(1). doi: 10.54933/jmbrp-2023-15-1-2

Introduction

The efficiency of financial services remains a topical economic discourse and dates back to earlier writers like Fama (1970) and Fama and French (1992). For financial series to be efficient, it is expected to reflect adequate market information, and to this end, weak form and strong form categorizations of efficiency have been identified in the literature. These two forms suggest the extent that both public and private information are accommodated in reflecting the true price of such financial series. An inefficient financial asset breeds arbitrage activities by speculators and gives room to abnormal as well as excessive profiteering when traded. In Nigeria, the foreign exchange market has been seriously balkanized, and allegations of wanton speculations have been levelled against players in the market. Specifically, the Bureau De Change operators have been accused of undue speculations that have resulted in wider disparities in the prices that the domestic currency exchanged for the internationally referenced currencies, especially the United States dollar. The arbitrage opportunities led foreign currency traders to prefer selling at the parallel market (otherwise known as the black market) window but buying at the interbank window. This brought about disequilibrium between the demand for and the supply of foreign currency in the Nigerian economy.

The disequilibrium of the demand for and supply of foreign currency has deteriorating implications for international trade and the balance of payment positions in the country. The height of this worrisome situation led the Central Bank of Nigeria (CBN) to suspend the activities of Aboki FX indefinitely for alleged illegal activity that undermines the economy in September 2021[1]. Aboki FX is a website that provides real-time data on the movements of exchange rates in Nigeria. Aboki FX is a window for tick-by-tick data related to the value of the domestic currency in terms of foreign currencies and internationally referenced currencies of United States dollar, pound sterling, yuan, franc, etc. Put differently, Aboki FX created a real-time data window for parallel market exchange rates of naira. The CBN alleged that owing to the news sentiments, the activities of this foreign exchange window have put pressure on the values of the domestic currency and have altogether made nonsense of the policy directives of the monetary authority. The issue really is not that Aboki FX traded foreign currencies and made speculations therefrom. However, the monetary authority alleged that the continual wide-range differentials between the parallel and interbank exchange rates created by such activities promote undue speculations and remain a matter of concern.

The CBN (2021) posited that the overall health of the Nigerian economy was relapsed on the exchange rate speculations due to the 'untrusted' real-time data provided by Aboki FX. The monetary authority posited that this was consequent upon investors' sentiments toward the news from this real-time source and making this reflects on the expected rate of exchange of the domestic currency. In the same token, it is expected that every financial series should fully reflect all available market information. The idea that Nigeria currently operates a managed-float exchange rate regime made the interbank rate fall short of full market information. However, the monetary authority has copiously argued that the exchange rate in Nigeria has been over-valued; hence, the need for intervention to obtain its right price. Although the activities of Aboki FX create big data for exchange rate determination in Nigeria, it has been alleged by the monetary authority that the speculative tendencies attributed to this data-generating process, owing to news sentiments, have

[1] See CBN (2021)

undermined this benefit. This study seeks to make inference about the role of big data in determining the efficiency of the exchange rate in Nigeria through a comparison between low-frequency and high-frequency data. The empirical literature has alluded to the potency of big data in economic analyses (see De Mol et al., 2017; Shen, 2021; United Nations ESCAP, 2021; Wibisono et al., 2019). The low-frequency data here would be the exchange rate in monthly and quarterly frequencies, while the daily data on the exchange rate serves as the high-frequency data. The efficiency parameter of these data frequencies will validate the role of big data, such as the real-time data provided by Aboki FX, in determining the efficient price of the exchange rate in Nigeria. More so, this study seeks to investigate the direction of causality between news sentiment and exchange rate in Nigeria, both for the low and high-frequency data.

Theoretical background and Empirical Review

The conceptual expositions for this study harp on efficiency, big data and news sentiment. Big data is a novel concept that describes varying, rich, updated and sufficient data-generating economic and financial series processes. On the other hand, financial asset efficiency usually hinges on information-full prices where prices of financial assets fully reflect all known information of the past, present and future, including private and public information. As news is uncertain, making information highly unpredictable, prices of financial assets are expected to follow a random walk process. Random walk is a term that describes a radical departure away from the previous trend of prices in the past. This suggests that the prices of financial assets cannot be obtained in any deterministic or characteristic pattern but follows through unpredictable as well as random walk process. Theoretically, there are three theoretical expositions on the efficiency market hypothesis. These are the fair game model, the martingale difference hypothesis and the random walk hypothesis. The fair game model hinged on the risk-return maxim that a financial series with a higher return should have a correspondingly high risk. This theory relies on the presumption of full utilisation of all available information. In addition to the full utilisation of available information, the equal distribution of successive changes in returns to financial series combined to form the third theory known as the random walk hypothesis. The second theory presumes that the predicted value of financial series can be, at least, equal to the current value subject to the projected information that exists.

The empirical literature on big data analytics exists in two major strands. The first strand relates to those studies that seek to examine the benefits and attendant opportunities that come with the use of big data for obtaining efficient and robust economic analyses. Big data promotes a systematised framework to study economic shocks and allow for the development of machine learning procedure to have in-depth analyses of the heterogeneous components of statistical models (Almeida, 2017; Balar and Chaabita, 2019). With big data, the forecasting abilities of economic models improve and policy choices become robust for far-reaching effects on economic agents, institutions and stakeholders (Balachandran and Prasad, 2017; Byers, 2015; Hersh and Harding, 2018). It is cost-effective and has high extrapolation power, lending credence to its high forecasting credibility. Despite these standard merits, economic analyses have not been at top speed with the pace of big data. There are many inherent factors, including the complexity of building a sophisticated model to accommodate the volume and versatility of big data. The quality and novelty requirements of big data are also important. Based on these, the general application of big data has suffered serious setbacks, and its applications to economic and financial analyses have been limited (Chavan and Akarte, 2014; Hammer, Kostroch, Quiros., and STA Group; 2017 AbdulKadri, Evans and Ash, 2016; Doerr, Gambacorta, and Serena, 2021).

The second strand of the literature are those studies that seek to employ the use of the behavioural model to investigate the robustness of empirical assessment on the attendant availability of big data. However, this strand of the literature has not enjoyed rich patronage as all the authors have employed the use of survey techniques, questionnaire administration, or just undertaken a literature review. Hassani and Silva (2015) reviewed the literature and found that the attributable techniques befitting of big data analytics in economics and financial studies include the network as well as neural models, factor models, forecasting models and Bayesian models. The study of Taylor, Schroeder and Meyer (2014) alluded to the innovative dimensions that big data brings to economic analysis. Creative thinking, novel techniques and robust analytics are some of the perspectives of big data. With big data, the conservative approach to theoretical modellings is revisited as more sophistication is brought to unveil realistic theoretical propositions.

Methodology

As earlier posited, there are five attributes of big data: volume, velocity, variety, veracity and value. This study seeks to employ daily, quarterly and yearly data frequency to meet the volume and velocity contents of Nigeria's exchange rate data. In terms of variety, the interbank foreign exchange market (IFEM) data would be employed for analyses, and inference would be made about the need for real-time data as available through the parallel market window. For veracity, only data on the exchange rate from credible sources would be used. The annual statistics of the Central Bank of Nigeria (CBN) would be consulted for these exchange rates data, and the value content of the price value of exchange rate data is predicated on the fact that it is useful for policymakers to identify arbitrage activities of speculators in the foreign exchange market. To strengthen the variety content, the price efficiency of the exchange rate in Nigeria will be spliced into different frequencies.

Since investment sentiments are also considered for this examination, the index computed by Bukman, Shapiro, Sudhof and Wilson (2020 as updated) is opted for, which is collected via the Federal Reserve Bank of San Francisco's database. The datapoints for the analysis span the period 2001 – 2022. This period is considered desirable, as it is long enough to address the dynamics of exchange rate using daily, quarterly and yearly data frequencies to elicit vital information about the price efficiency of the exchange rate in Nigeria. Traditionally, the efficiency of financial series can be ascertained using graphical trends. However, this study employs three approaches of analyses: graphical analysis, descriptive analysis, and the use of a data stability test together with a variance ratio test. A comparison of the price efficiency of the exchange rate would be made across these different data frequencies.

The test for unit root for a variable S is carried out using the following specification:

$$\Delta S_t = \beta_0 + \beta_{it} + \beta_2 S_{t-1} + \sum_{i=0}^{p} \varphi_i \Delta S_{t-i} + \varepsilon_t \tag{1}$$

Where β_0, β_1, β_2 and ψ_i-------------ψ_p are parameters to be estimated, and ε_t is normally and identically distributed.

The framework for the pair-wise granger causality is given below as

$$EXCHR_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} EXRVOL_{t-i} + \sum_{i=1}^{k} \delta_{1i} INVS_{t-i} + \upsilon_{1t}$$

$$INVS_t = \beta_0 + \sum_{i=1}^{k} \beta_{1i} INVS_{t-i} + \sum_{i=1}^{k} \phi_{1i} EXCHR_{t-i} + \upsilon_{2t} \tag{2}$$

Results

The trend depicted in Figure 1 is highly instructive as it demonstrates how changes in exchange rates also translate to corresponding changes in returns. There are periods of a substantial rise in the exchange rate of the domestic currency to the internationally referenced currency of the United States dollar. The exchange rate increased tremendously in the periods 2008, 2014, 2016, 2018 and 2020. Two important occurrences within these periods are the global economic cum financial crisis of 2007 – 2009 and the global health emergency of the COVID-19 pandemic that occurred in December 2019. Evidently, too, the stock market crash of 2016 is another economic scenario that crashed the domestic currency. Precisely, the domestic currency exchange for above N150 to US$1 in 2008, about N200 in 2014, around N300 in 2016 and gravitated to N350 in 2018, prior to the global pandemic, and has climbed to above N400, since the global pandemic in 2019 (see Figure 1).

As evident, the effects of global crises on the value of exchange rates in Nigeria cannot be disregarded. However, the fact that the highest depreciation of the domestic currency occurred in 2016 is an indication that the factors endangering the domestic currency is an inherent and endogenous factor(s). This lends credence to the assertion that perhaps wanton speculations by traders in the exchange rate markets could be instrumental to its abysmal performance with other internationally referenced currency, the chief of which is the United States dollar. Interestingly, the returns corresponding to the depreciation of the domestic currency also increase, even more than the increase in the exchange rate of the domestic currency itself. This provides insight into the efficiency issues that this study seeks to investigate. In an efficient market, there is no room for any arbitrage activity that would permit any of the players to gain supernormal profits and/or returns, as is the case with the exchange rate of the naira to the United States dollar.

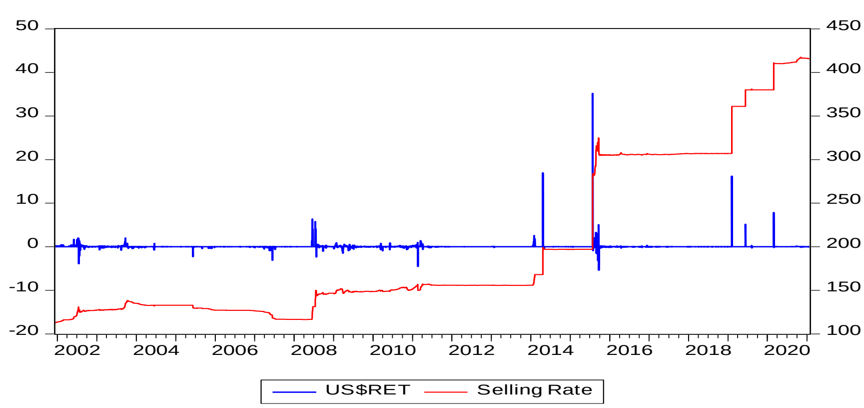

Figure 1: Value and Returns of Exchange Rate in Nigeria (12/10/2001 – 5/13/2022)
Source: Authors

Interestingly, the study seeks to investigate the role of investors' sentiments in the efficiency behaviour of the exchange rate. News sentiments are the sentiments professed by investors during their portfolio balancing decisions, hence, otherwise known as investment sentiments. As depicted in Figure 2, the investment sentiments are well suited as the investors became most pessimistic during the periods of the global financial crisis of 2007 – 2009 and the COVID-19 global pandemic. Investors cast a more pessimistic view during the period of the global pandemic. As there was to be a ray of investment optimism by October 2021, but this was short-lived as the investment sentiments reclined again in November 2021 and since March 2022 (see Figure 2).

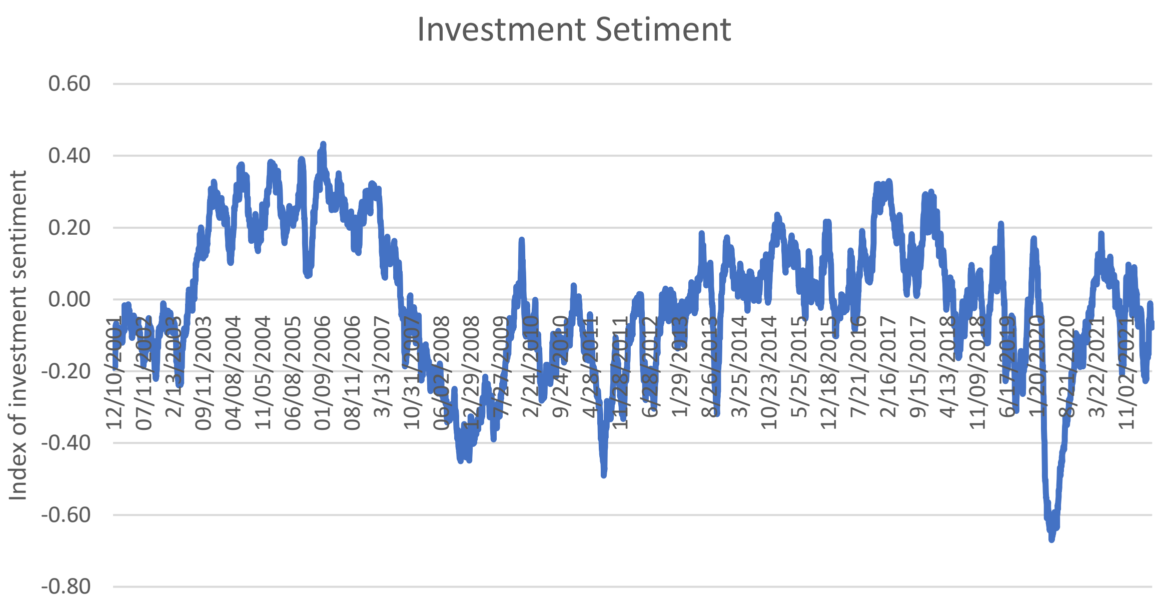

Figure 2: Investment Sentiments. Source: Authors with data sourced from Bukman, Shapiro, Sudhof and Wilson (2020 as updated). Federal Reserve Bank of San Francisco

The period 2003 – 2007 has been that where the investors have been optimistic about their portfolio balancing decisions. Coincidentally, the value of the exchange rate and the corresponding returns were relatively stable during this period. The returns on exchange rate trading during this period were near zero. Zero exchange rate returns indicate that there were no excessive arbitrage activities of the exchange rate during the period 2003 – 2007 that would allow investors to make abnormal returns as compared to other periods. Stemming from these trend analyses, this study seeks to investigate how investment sentiment granger causes the depreciation of the exchange rate in Nigeria. More so, the study would ascertain if the exchange rate has been efficient in Nigeria for the period under consideration. To pursue the objective of ascertaining the exchange rate efficiency in Nigeria, conventional and modified unit-root, as well as stationary tests, have been estimated (see Tables 1 – 3). The decision rule is that a financial series that is of, at least weak-form efficiency; would be unit-root. This denotes a random walk behaviour of the exchange rate as it is expected to be independent of past events. As detailed in Table 1 -3, the exchange rate in Nigeria is of weak-form efficient. This suggests that the exchange rate follows a random walk pattern and cannot be predictable for abnormal profits by investors engaging in wanton arbitrage activities.

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ISSN 1339-9381

Table 1: Unit-Root Test for Investment Sentiments and Exchange Rate Efficiency in Nigeria – Daily Data

<table>
<tr><th colspan="9">Conventional Unit Root Test</th></tr>
<tr><td></td><th colspan="5">ADF</th><th colspan="3">PP</th></tr>
<tr><td>Variables</td><td colspan="2">T- Statistics</td><td colspan="2">P Value</td><td>Decision</td><td>T- Statistics</td><td>P Value</td><td>Decision</td></tr>
<tr><td>Exchange Rate</td><td colspan="2">-70.35* (I(1))</td><td colspan="2">0.0001</td><td>Weak-form Efficient</td><td>-70.35* (I(1))</td><td>0.0001</td><td>Weak-form Efficient</td></tr>
<tr><td>Investment Sentiment</td><td colspan="2">-3.84* (I(0))</td><td colspan="2">0.0025</td><td>Not weak form efficient</td><td>-3.71* (I(0))</td><td>0.0040</td><td>Not weak form efficient</td></tr>
<tr><td></td><th colspan="5">KPSS</th><td></td><td></td><td></td></tr>
<tr><td>Variables</td><td colspan="4">LM Stat</td><td>Decision</td><td></td><td></td><td></td></tr>
<tr><td>Exchange Rate</td><td colspan="4">0.45* (I(1))</td><td>Weak-form Efficient</td><td></td><td></td><td>Weak-form Efficient</td></tr>
<tr><td>Investment Sentiment</td><td colspan="4">0.66* (I(0))</td><td>Not weak form efficient</td><td></td><td></td><td>Not weak form efficient</td></tr>
<tr><th colspan="9">Modified Unit Root Test</th></tr>
<tr><td></td><th colspan="5">Dickey-Fuller GLS</th><th colspan="3">Elliot Rothenberg Stock Point Test</th></tr>
<tr><td>Variables</td><td colspan="4">Elliott-Rothenberg-Stock DF-GLS test statistic</td><td>Decision</td><td colspan="2">Elliot Rothenberg Stock Test Statistic</td><td>Decision</td></tr>
<tr><td>Exchange Rate</td><td colspan="4">-70.26* (I(1))</td><td>I(1)</td><td colspan="2">0.01</td><td>Weak-form Efficient</td></tr>
<tr><td>Investment Sentiment</td><td colspan="4">-2.96* (I(0))</td><td>I(0)</td><td colspan="2">1.39</td><td>Not weak form efficient</td></tr>
<tr><td></td><th colspan="4">NG Perron</th><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td colspan="4">NG Perron Test Stat</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Variables</td><td>MZa</td><td>MZt</td><td>MSB</td><td>MPT</td><td>Decision</td><td></td><td></td><td></td></tr>
<tr><td>Exchange Rate</td><td>-2494.43*</td><td>-35.32*</td><td>0.01*</td><td>0.01*</td><td>Weak-form Efficient</td><td></td><td></td><td></td></tr>
<tr><td>Investment Sentiment</td><td>-17.78*</td><td>-2.98*</td><td>0.17*</td><td>1.40</td><td>Not weak form efficient</td><td></td><td></td><td></td></tr>
</table>

Source: Authors' Computations

Note: *, **, * imply the series' stationarity at 1%, 5% and 10%, respectively. Likewise, ADF, PP and KPSS stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests, respectively.**

Table 2: Unit-Root Test for Investment Sentiments and Exchange Rate Efficiency in Nigeria – Quarterly Data

Conventional Unit Root Test								
	ADF					**PP**		
Variables	T- Statistics		P Value		Decision	T- Statistics	P Value	Decision
Exchange Rate	-5.97* (I(1))		0.00		Weak-form Efficient	-5.84* (I(1))	0.00	Weak-form Efficient
Investment Sentiment	-2.97** (I(0))		0.04		Not weak form efficient	-2.93** (I(0))	0.046	Not weak form efficient
	KPSS							
Variables	LM Stat				Decision			
Exchange Rate	0.048* (I(1))				Weak-form Efficient			
Investment Sentiment	0.12* (I(0))				Not weak form efficient			
Modified Unit Root Test								
	Dickey-Fuller GLS					**Elliot Rothenberg Stock Point Test**		
Variables	Elliott-Rothenberg-Stock DF-GLS test statistic				Decision	Elliot Rothenberg Stock Test Statistic		Decision
Exchange Rate	-5.94* (I(1))				Weak-form Efficient	0.74* (I(1))		Weak-form Efficient
Investment Sentiment	-2.68* (I(0))				Not weak form efficient	2.27** (I(0))		Not weak form efficient
	NG Perron							
	NG Perron Test Stat							
Variables	MZa	MZt	MSB	MPT	Decision			
Exchange Rate	-33.09*	-4.07*	0.12*	0.75*	Weak-form Efficient			
Investment Sentiment	-12.05*	-2.45**	0.20**	2.04**	Not weak form efficient			

Source: Authors' Computations

Note: *, **, * imply the series' stationarity at 1%, 5% and 10%, respectively. Likewise, ADF, PP and KPSS stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin test, respectively.**

Table 3: Unit-Root Test for Investment Sentiments and Exchange Rate Efficiency in Nigeria – Yearly Data

Conventional Unit Root Test								
	ADF					**PP**		
Variables	T- Statistics			P Value	Decision	T- Statistics	P Value	Decision
Exchange Rate	-5.092978* (I(1))			0.0038	Weak-form Efficient	-2.158** (I(1))	0.0330	Weak-form Efficient
Investment Sentiment	-4.284625* (I(0))			0.0039	Not weak form efficient	-4.284 (I(0))	0.0039	Not weak form efficient
	KPSS							
Variables	LM Stat				Decision			
LOG(Exchange Rate)	0.346215* (I(1))				I(I)			
Investment Sentiment	0.077890* (I(0))				I(0)			
Modified Unit Root Test								
	Dickey-Fuller GLS					**Elliot Rothenberg Stock Point Test**		
Variables	Elliott-Rothenberg-Stock DF-GLS test statistic				Decision	Elliot Rothenberg Stock Test Statistic		Decision
Exchange Rate	-5.158861 (I(1))				Weak-form Efficient	1.668989* (I(1))		Weak-form Efficient
Investment Sentiment	-4.399597 (I(0))				Not weak form efficient	2.436411** (I(0))		Not weak form efficient
	NG Perron							
	NG Perron Test Stat							
Variables	MZa	MZt	MSB	MPT	Decision			
Exchange Rate	-50.9159*	-5.01*	0.09845*	1.94669*	Weak-form Efficient			
Investment Sentiment					Not weak form efficient			

Source: Authors' Computations

Note: *, **, * imply the series' stationarity at 1%, 5% and 10%, respectively. Likewise, ADF, PP and KPSS stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin test, respectively.**

On the other hand, investment sentiments are not weak form efficient as the series shows a level of stationarity across all the various data dimensions – daily, quarterly and yearly. This implies that investment sentiments are highly predictable. As depicted in Figure 2, the investment sentiments follow the expectation of ongoing economic issues such as the global financial crisis of 2007 – 2009 and the COVID-19 global pandemic. The variance ratio test also confirms that the exchange rate is of weak form efficient both for both daily and quarterly data. The probability value could not reject random walk behaviour at the 5 percent level of significance as both has probability values of 0.999 and 0.098, respectively. However, the estimates of the yearly data frequency show that the yearly exchange rate is not weak-form efficiency as the probability value of 0.01 is lesser than the 0.05 level of significance (see Figure 4a). Therefore, it indicates the null hypothesis of random walk is rejected at the 5 percent level. These findings lend credence to the fact that big data, as produced by the Aboki FX real-time data, would only show the efficiency of the exchange rate in Nigeria and could not adduce abnormal returns to investors even during wanton arbitrage activities.

Table 4a: Variance Ratio Test for Exchange Rate Efficiency in Nigeria

Daily			**Quarterly**			**Yearly**		
Joint Tests	**Value**	**Prob.**	**Joint Tests**	**Value**	**Prob.**	**Joint Tests**	**Value**	**Prob.**
Max [z] at period 16	0.136	0.999	Max [z] at period 8	2.237	0.098	Max [z] at period 8	3.022	0.01

Source: Authors' Computations

On the other hand, investment sentiments are only of weak-form efficient for the quarterly and yearly data frequencies. The daily data frequency suggests that it is not weak form efficient when done on a daily basis.

Table 4b: Variance Ratio Test for the Efficiency of Investment Sentiments in Nigeria

Daily			**Quarterly**			**Yearly**		
Joint Tests	**Value**	**Prob.**	**Joint Tests**	**Value**	**Prob.**	**Joint Tests**	**Value**	**Prob.**
Max [z] at period 16	11.358	0.000	Max [z] at period 4	0.904	0.838	Max [z] at period 8	1.077	0.734

Source: Authors' Computations

From the foregoing, it is imperative to emphasise that this study conforms to the results in previous studies that big data increases the forecasting ability and the efficiency parameter of financial and economic dynamics. Empirical studies that stressed this submission include Hassani and Silva (2015); Taylor, Schroeder, and Meyer (2014); Almeida (2017); Balar and Chaabita (2019); Balachandran and Prasad (2017); Byers (2015); Hersh and Harding (2018). The implication is that the modelling framework for exchange rate efficiency should pattern its intrinsic data-generating frequency as well supported with the use of big data.

Consequent upon this, this study seeks to investigate the direction of causality between investment sentiments and exchange rate dynamics in Nigeria. To achieve this, pair-wise granger causality tests conducted have been tabulated below for the various data dimension. The estimates of the granger causality test for daily data are detailed in Table 5, for the quarterly data frequency is detailed in Table 6 and the yearly data frequency is in Table 7.

Table 5: Granger Causality for Daily Exchange Rate Data in Nigeria

Null Hypothesis:	Obs	F-Statistic	Prob.
INVESTMENT_SETIMENT does not Granger Cause D(EXCHANGE_RATE)	4988	2.55391	0.0779
D(EXCHANGE_RATE) does not Granger Cause INVESTMENT_SETIMENT		0.14397	0.8659

Source: Authors' Computations

The granger causality test suggests that there is no causal link between investment sentiments and exchange rate depreciation in Nigeria. The null hypothesis that there are no granger causalities between these two variables cannot be rejected at the 5 percent level of significance. (Tables 5 – 7). As a result, this study could not find evidence to ascribe the depreciation of the domestic currency to investment sentiments, part of which include speculations on the basis of domestic and global economic cum financial dynamics. This result is striking and instructive enough about investors making their decisions and the policy directions from the regulatory authorities, including the monetary authority – the Central Bank of Nigeria.

Table 6: Granger Causality Test for Quarterly Exchange Rate Data in Nigeria

Null Hypothesis:	Obs	F-Statistic	Prob.
INVESTMENT_SETIMENT does not Granger Cause D(EXCHANGE_RATE)	75	0.471	0.626
D(EXCHANGE_RATE) does not Granger Cause INVESTMENT_SETIMENT		2.3991	0.098

Source: Authors' Computations

Table 7: Granger Causality Test for Yearly Exchange Rate Data in Nigeria

Null Hypothesis:	Obs	F-Statistic	Prob.
INVESTMENT_SETIMENT does not Granger Cause D(EXCHANGE_RATE)	18	0.527	0.6023
D(EXCHANGE_RATE) does not Granger Cause INVESTMENT_SETIMENT		1.053	0.3769

Conclusion

The study engaged big data to investigate foreign exchange efficiency in Nigeria, accounting for the role of news as well as investment sentiments. The study found evidence for the efficiency of the exchange rate both for daily and quarterly data frequencies but not for the yearly data. That this evidence holds at a higher frequency of exchange rate data but not at a lower frequency confirms that the variability and voluminous nature of the data used for investigation would determine to what extent exchange rate prices would reflect market information and represent its true price. However, there was no evidence that investment sentiments (that is, the extent of pessimism or optimism of the investors) drive the dynamics of the exchange rate in Nigeria, as the null hypothesis of no granger causality could not be rejected. Consequent to these insights, this study, therefore, recommends that;

(a) Larger datasets for exchange rates through real-time arrangement would rather stimulate exchange rate efficiency as against making it overvalued. As such, the monetary authority is enjoined to create a very rich real-time data platform as Aboki FX which was suspended in September 2019. Investors would obtain current and instantaneous information on the value of the exchange rate.

(b) Investment sentiments are found not to be subjective as they reflect essential domestic cum global dynamics. As such, it should not be discountenanced as wanton speculations by the monetary authority to clamp down on Bureau De Change (BDC) market in the country.
(c) That the study could not obtain evidence that investment sentiment granger causes exchange rate dynamics in the country further corroborate the possibility that exchange rate dynamics react to other market fundamentals.

The implication of these results is that following its data-generating process, the exchange rate is efficient in Nigeria. Hence, the monetary authority should promote real-time information about exchange rate value in Nigeria to reduce speculations that would promote excessive returns on arbitrage activities by investors. In addition, this study implies that the monetary authority in Nigeria should model exchange rate efficiency around its intrinsic data-generating frequency, as supported by big data analyses in this study. Within the global context, the efficiency of the exchange rate in Nigeria would indicate there would not be much difference between the spot rate and the future rate of the exchange rate. Therefore, importations by manufacturers would not experience huge spikes within the shortest possible time, and there would not be price distortions within the domestic economy. Nonetheless, the implications of these policy suggestions have to be taken with caution owing to issues that would have limited the extent of reliability and validity of the estimates obtained. The following areas are suggested for further studies.

(i) Real-Time Parallel Market Exchange Rate Data: In order to properly situate the role of big data, this study suggests that a comparison should be made between exchange rate data obtained from the parallel market and interbank windows. This is to further enrich the conclusion reached in this study and will further assist in justifying the role of speculations in determining the efficiency of the domestic currency with reference to the internationally referenced currencies of the United States dollar, China Yuan, United Kingdom pound sterling and others.

(ii) Accounting for Structural Breaks: This study suggests a way to embellish the decision on exchange rate efficiency is to account for the role of structural breaks. Within the period under review, the global economic crisis of 2007 – 2009 and the recent global health emergency have been observed to compound news sentiments across the globe.

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JOURNAL OF MANAGEMENT AND BUSINESS: RESEARCH AND PRACTICE
2023 15(1) ISSN 1339-9381

THE RELATIONSHIP AMONG GOALS, LEARNING STRATEGIES, AND SELF-EFFICACY BELIEFS. STRUCTURAL MODELING APPROACH

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Received: January, 2023
1st Revision: February, 2023
Accepted: April, 2023

ABSTRACT.
Background - Learning is a necessity for everyone, including employees. Many employees in Indonesia choose to continue their studies for self-development. This is inseparable from the learning strategy chosen. **Aims -** This study aims to investigate the relationship between the three models of achievement goals, learning strategies, and self-efficacy beliefs. **Methods -** Correlation analysis for testing the relationship between variables in accordance with the study hypothesis was carried out after the questionnaire was declared valid and reliable. A SEM with a two-step approach was used to test the relationship model simultaneously. **Sample -** The study was conducted with 506 university working students participating in undergraduate programs in economics and business in Indonesia using a survey questionnaire. **Results -** The model that was found to be the most appropriate was self-efficacy beliefs, which mediated the relationship between achievement goals and learning strategies. The mastery approach was a dimension of achievement goals that consistently and positively influenced each other with deep learning strategies and self-efficacy beliefs. The beliefs also consistently and negatively influenced each other with surface learning strategies. **Conclusions** - The result indicated a consistent relationship and influence between mastery goals, deep learning strategies, as well as self-efficacy beliefs or between performance-avoidance goals, surface learning strategies, and self-efficacy beliefs. **Implications -** This study also strengthened the understanding that individuals with high self-efficacy beliefs have a goal to outperform their peers but are inconsistent in the selection of strategies.

Keywords: mastery approach goals, performance approach goals, performance avoidance goals, deep learning strategies, surface learning strategies, self-efficacy beliefs

***JEL Classification**:* example D02, O17, P31

DOI: 10.54933/jmbrp-2023-15-1-3

Ariani, D.W. (2023). *The Relationship among Goals, Learning Strategies, and Self-Efficacy Beliefs. Structural Equation Modeling Approach*. Journal of Management and Business: Research and Practice, 15(2), 11-25. doi: 10.54933/jmbrp-2023-15-1-3

Introduction

Contemporary studies repeatedly showed that non-cognitive factors such as motivation affect performance (Lee & Stankov, 2013). This is because it plays an important role in predicting attitudes, strategies, and efforts to set goals for achieving high performance (Jiang et al., 2014). Jiang et al. (2014) showed that the motivational construct with the strongest effect on performance was achievement goals. Meanwhile, some studies showed that there was a relationship between achievement goals, self-efficacy, and learning strategies (e.g., Kahraman & Sungur, 2013; Prat-Sala & Redford, 2010). Furthermore, these variables have a mutually influencing relationship and were also discovered to affect academic achievement (Herrmann et al., 2017; Soylu et al., 2017).

Motivation has been considered for a long time as the most important concept in education (Herath, 2015). Research teams still pay a lot of attention to motivation in the learning context, especially in developing student motivation. They also conducted studies with university students as participants to understand their motivation in academic settings (e.g., Kahraman & Sungur, 2013; Linnenbrink-Garcia & Barger, 2014). Several views about the learning process are based on achievement goal theory (AGT), self-determination theory (SDT), and social cognitive theory (SCT) of motivation in various settings, including universities and workplaces (Mesmer-Magnus & Viswesvaran, 2010). AGT has been the most widely used motivation theory for more than three decades. Goal theory places mastery goals orientation (MGO) and performance goals orientation (PGO) in influencing various educational outcomes (e.g., Chen & Wong, 2015; Huang, 2012; Steinmayr et al., 2011). Studies conducted on this subject in Western countries and Asian contexts have provided much and varied empirical support for using the framework (King & Ganotice, 2013).

In addition to achievement goals, self-efficacy beliefs (SEBs) are also motivational variables. It is the main construct in SCT which refers to beliefs and considerations related to their ability to complete tasks (Azar et al., 2010). SEBs are mainly used when individuals find tasks or jobs difficult (Bong et al., 2010), while achievement goals are adopted in certain situations (Jiang et al., 2014). The results showed that there was a relationship between learning strategies, SEBs, and learning outcomes (e.g., Herrmann et al., 2017; Richardson et al., 2012).

Meanwhile, learning strategy is a determining factor in academic performance and knowledge acquisition besides motivation (Cano et al., 2018; Everaert et al., 2017; Garcia et al., 2016). It is also dynamic and used to achieve learning goals that can develop rapidly (Zlatovix et al., 2015). Student Approach to Learning (SAL) has proposed two different learning strategies, namely deep learning strategies (DLS) and surface learning strategies (SLS) (Fryer & Ginns, 2017; Richardson, 2015). The former prioritizes understanding the material, while the latter prioritizes memorizing or repeating material (Cano et al., 2018; Heikkila et al., 2012).

The relationship between motivation, strategies in the learning process, and learning achievement has not been adequately examined since the existing study is limited to the western context (Cano & Berben, 2008). Empirical studies on this matter in the context of non-western culture are expected to provide added value that broadens understanding of the need for motivation and goals in student learning outcomes. This study aims to examine the relationship between achievement goals, learning strategies, and SEBs to understand how students achieve academic performance. The question that arises is whether the students' learning goals and strategies have an effect on estimating their academic performance or whether the strategy is chosen after the students know their academic performance. There are three models tested in this study. First, learning strategies mediate the relationship between achievement goals and SEBs as perceived performance. Second, SEBs mediate the relationship between achievement goals and two learning strategies. Meanwhile, the third model, achievement goals, mediates the relationship between SEBs and learning strategies.

Theoretical background

According to Hulleman et al. (2010), achievement goals orientation (AGO) is defined as future cognitive goals that direct competency-related behaviors in which individuals commit to approaching or avoiding the expected final state. It is also the core construct for motivation studies in achievement settings. The approach is conceptualized as cognitive-dynamic goals that focus on competence. Meanwhile, achievement experts define mastery goal orientation (MGO) as developing individual competencies and performance goal orientation (PGO) as showing individual competencies by outperforming their peers (Senko et al., 2011). Both goals are pursued by students during their learning process because they are not being mutually exclusive and do not contradict (Martinez-Monteagudo et al., 2018). Therefore, individuals may have two goal orientations and they can be characterized accordingly. They can provide principles that underlie strategies for learning. The multiple goals view states that students can simultaneously use multiple goals in school settings (Wormington & Linnenbrink-Garcia, 2017).

There are two main dimensions of achievement goals, each of which has an approach and an avoidance dimension. AGO is divided into four dimensions, namely mastery-approach goal orientations (MApG), mastery-avoidance goal orientations (MAvG), performance-approach goal orientations (PApG), and performance-avoidance goal orientations (PAvG), they are independent but correlated with each other (e.g., Duchesne et al. 2017; Hackel et al., 2016). Several studies showed that approach and avoidance goals are associated with positive and negative outcomes, respectively (e.g., Linnenbrink-Garcia et al., 2012; Zhou & Wang, 2019). MApG (motivate to master the material and increase knowledge) consistently tends to be associated with positive outcomes (Pantziara & Philippou, 2014; Scherrer et al., 2020). Meanwhile, PAvG (avoid failure in front of others) is consistently associated with less adaptive outcomes (Hall et al., 2016; Turner et al., 2021). PApG studies reported inconsistent results (Senko et al., 2013). Some studies stated that PApG (shows relative competence to others) was associated with positive outcomes (Senko & Dowson, 2017; Zhou & Wang, 2019) while some disagreed Daniels et al., 2009).

Furthermore, MAvG (avoid situations where the individual is unable to learn) is rarely used because it is difficult to conceptualize (Gore, 2014). Until now, it is still poorly understood how students interpret MAvG (Linnenbrink-Garcia & Barger, 2014). Usually, this goal orientation is associated with maladaptive outcomes (Bjornebekk et al., 2013). Senko and Freund (2015) stated that MAvG is not always detrimental. It is chosen when the material to be studied is difficult, not well understood, or students are still in the first semester of college (Turner et al., 2017). Previous studies suggested that adopting MAvG is not as important as adopting MApG (Baranik et al., 2010) or as important as PApG and PAvG (DeShon & Gillespie, 2005). Although it did not get much support from subsequent research teams, VanYperen (2006) discovered that it could improve achievement goals. Therefore, the MAvG dimension was not used in this study. It is not as prominent as the other achievement goals dimension because the construct and predictive validity of this dimension is relatively unknown (Baranik et al., 2010).

In addition to achievement goals which are motivational variables, learning strategy is a key factor influencing academic achievement (Chen et al., 2015). Studies on the relationship between learning strategies and achievement goals still need to be conducted. Achievement goals are sensitive to contextual influences on learning (Dinger & Dickhauser, 2013) and learning strategies (Paulick et al., 2013). The research team stated that the relationship between the two constructs was proven in empirical studies (e.g., Asikainen & Gijbels, 2017; Luftenegger et al., 2016; Martinez-Monteagudo et al., 2018). Each MGO and PGO has consequences. Individuals may pursue different achievement goals because they are driven by specific achievement motivations related to their culture (Abd-El-Fattah & Patrick, 2011). Individuals who adopt MGO generally have adaptive behaviors, such as having a large business and using deep or meaningful learning strategies (King & Ganotice, 2013).

Students' learning strategies or approaches are divided into two general categories, namely low or surface-level strategies (SLS) and high or deep level strategies (DLS) (Kadioglu & Kondakci, 2014). They are both mutually exclusive strategies (Everaert et al., 2017). At DLS, students try to understand what is learned. This is carried out by involving thinking and integration between learning components and assignments. Furthermore, it includes deep motives, such as an interest in ideas or learning, while SLS includes motives for fear of failure and using rote learning strategies without using ideas (De la Fuente et al., 2017). DLS includes a rehearsal strategy, while the alternative includes elaboration and organization (Kadioglu & Kondaksi, 2014). It also requires a higher cognitive level and helps conceptual understanding, while SLS is used for simple tasks, such as remembering and repeating information until students remember (Luftenegger et al., 2016).

Logically, both learning strategies can comprehensively improve attainment grades (Cano et al., 2018; Everaert et al., 2017). Fox et al. (2010) affirmed that successful students will adopt both by combining an understanding of the material and organizing studies or awareness of assessment requirements. Motivation and learning strategies are related to one another, therefore, they can explain academic performance (Garcia et al., 2016). MGO is associated with a set of positive and adaptive affective processes, such as adopting DLS, whereas PGO is considered maladaptive and is associated with negative motivation and cognition like the use of SLS (Martinez-Monteagudo et al., 2018). Several studies indicated that there was a positive relationship between DLS and performance (e.g., Chen et al., 2015; Herrmann et al., 2017; Murayama et al., 2013; Shearer et al., 2015) or a negative relationship between SLS and performance (e.g., Baeten et al., 2010; Garcia et al., 2016;

Yaratan & Kasapoglu, 2012). Meanwhile, Elias (2005) discovered no significant effect of DLS on performance but confirmed the negative relationship between SLS and academic achievement. Students with DLS and those with SLS aim to understand and reproduce the material, respectively (Everaert et al., 2017).

Furthermore, a relationship between achievement goals, learning strategies, and SEBs was also discovered (e.g., Mason et al., 2013; Pantziara & Philippou, 2014; Turner et al., 2021). SEBs are beliefs that they can do well in an academic setting, feel comfortable, never give up, and perform better (Bandura, 1997). It refers to individuals' thoughts that they can successfully achieve a certain performance level (Pantziara & Philippou, 2014). It was also stated that high and low SEBs were related to approach and avoidance goals, respectively (Lee & Mao, 2016). Meanwhile, some studies showed that the beliefs were antecedent achievement goals (Azar et al., 2010) however, some indicated that they were consequences of achievement goals Mentis-Koksoy & Aydiner-Uygun, 2018). SEBs are also influenced by DLS and SLS (Aydiner-Uygun, 2020; Cano et al., 2018).

Some studies concentrated on the relationship between AGO and learning strategies or grades in the class (e.g., Geitz et al., 2015; Koopman et al., 2014). As motivation variables, AGO also arouses individuals to choose learning strategies or approaches (Chai et al., 2016; Rashid & Rana, 2019). Furthermore, culture influences the learning strategies used (McLaughin & Durrant, 2017). There is evidence that educational outcomes are related to learning strategies (e.g., Everaert et al., 2017; Senko et al., 2013; Wyn-Williams et al., 2016). In an educational concept, DLS relates to MGO, SLS to PGO (Aydiner-Uygun, 2020; Chen et al., 2015; Chotitham et al., 2014; Herrmann et al., 2017; Geitz et al., 2015; Ohrstedt & Lindfors, 2019), while PApGO and PAvGO relate to SLS (Abd-El-Fatta, 2018; Ferla et al., 2010). High SEBs are associated with MGO and PApG, but usually, only individuals with MGO use DLS, while SLS is associated with low SEBs and PavG (Azar et al., 2010; Prat-Sala & Redfort, 2010).

Based on previous studies, there are three models of the relationship that can be developed between these variables. The first model is learning strategies mediating the relationship between achievement goals and self-efficacy as perceived performance. In other words, achievement goals affect the selection of learning strategies used, while learning strategies affect SEBs.

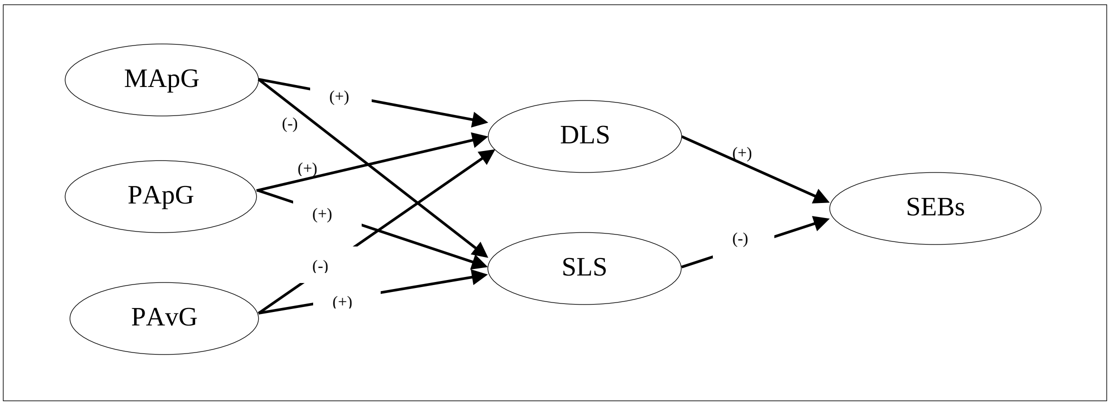

Figure 1. First Model: Learning Strategies Mediate the Effect of Achievement Goals on Self-Efficacy Beliefs

Zubkovic and Kolic-Vehovec (2014) stated that achievement goals are predictors of strategies used in learning. Students adopt learning strategies after setting achievement goals, hence, the right learning strategies can produce achievements. Empirical evidence showed that the goals pursued by students are related to the learning strategies used (e.g., Abd-El-Fatta, 2018; Everaert et al., 2017). Broadbent and Poon (2015) showed a relationship between motivation, strategy, and learning achievement. Learning strategies play a mediator role in the relationship between motivation and learning performance (Lin et al., 2017; Zhou & Wang, 2019). Lin et al. (2017) and Wang et al. (2013) explicitly stated that goal orientation affects performance through learning strategies.

The second model, SEBs mediates the relationship between achievement goals and two learning strategies. Achievement goals have different effects on SEBs (Hiver & Al-Hoorie, 2016; Turner et al., 2021). Furthermore, learning strategies selection is carried out after the students can perceive their academic abilities. Individuals who perceive high abilities will choose a DLS, while those who perceive low abilities will adopt an SLS (Ohrstedt & Lindfors, 2016).

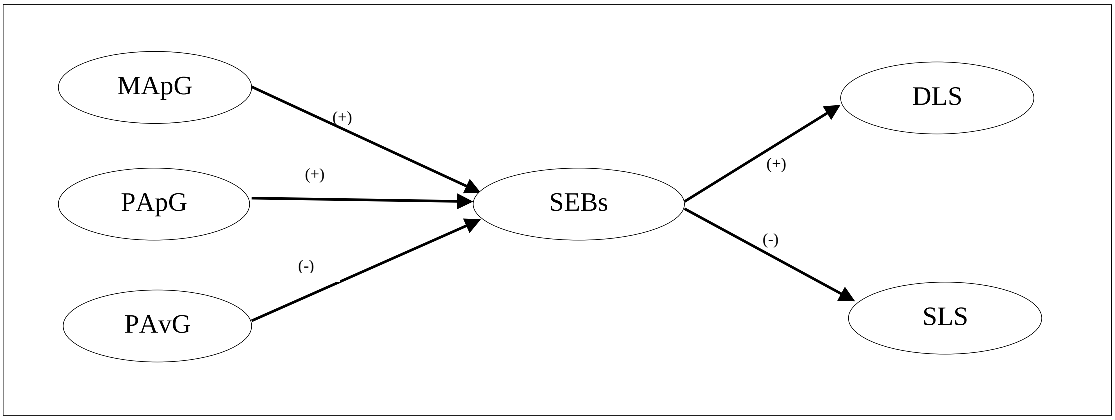

Figure 2. Second Model: Self-Efficacy Beliefs Mediate the Effect of Achievement Goals on Learning Strategies

The effect of goal orientation on academic achievement has been studied extensively (e.g., Huang, 2012; Zhou & Wang, 2019). Academic achievement is not only a grade point average (GPA) but can be a student's ability perception (self-efficacy) which involves the perception of personal abilities to achieve the expected results (Bong & Skaalvik, 2003). Goal orientation uniquely affects perceived performance or SEBs (Bipp & van Dam, 2014; Bjornehekk et al., 2013; Diseth & Kolbeltvedt, 2010; Scherrer et al., 2020). Generally, MApG and PAvG have positive and negative effects on SEBs, respectively (e.g., Mason et al., 2013; Mentis-Koksoy & Aydiner-Uygun, 2018; Senko et al., 2013). The effect of PApG on SEBs is inconsistent. Several studies showed that it had a positive effect (e.g., Chen & Wong, 2015; Honicke & Broadbent, 2016; Senko & Dowson, 2017). Students with MApG and PAvG usually use DLS and SLS, respectively (Shyr et al., 2017). In addition, individuals with high SEBs prefer DLS to SLS (Gargallo et al., 2015).

The third model, achievement goals, mediates the relationship between SEBs and learning strategies. It shows that the achievement goals are based on students' perceptions of the goals to be achieved. Students will set goals to increase and deepen their knowledge or show ability beyond their peers when they believe in their abilities. Meanwhile, they will set goals to avoid appearing incapable when indeed, they feel that they are not capable.

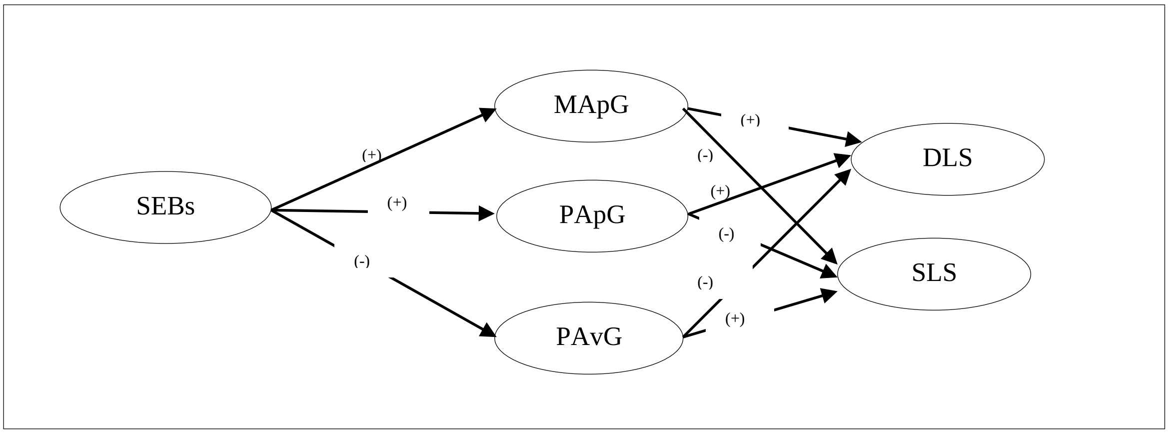

Figure 3. Third Model: Achievement Goals Mediate the Effect of Self-Efficacy Beliefs on Learning Strategies

When students believe that they can achieve high performance, they will choose higher goal achievement or set goals for mastery of the material (Honick & Broadbent, 2016; Jiang et al., 2014). Also, students with high SEBs will adopt MApG and PApG, while those with low SEBs will adopt PAvG (Liem et al., 2008; Kizilgunes et al., 2009). Meanwhile, MApG positively influences DLS (Azar et al., 2010), and in an educational context, MGO is associated with DLS and PGO with SLS (Shyr et al., 2017). MGOs can predict learning strategies, while PGOs do not because they are negatively correlated with achievement (Pantziara & Philippou, 2014). Mastery-oriented students process learning information at a deep level (e.g., Aydiner-Uygun, 2020; Koopman et al., 2014; Mason et al., 2013; Shyr et al., 2017; Soyer & Kirikkanat, 2018; Zubkovic & Kolic-Vehovec, 2014). Meanwhile, the PGO relationship is diverse and controversial (De la Fuente et al., 2017; Zhou &Wang, 2017). PApG relates to the use of SLS (e.g., Abd-El-Fatta, 2018; Hoffman et al., 2019; Koopman et al., 2014; Senko et al., 2013, Shearer et al., 2015) and DLS (e.g., Abd-El-Fatta, 2018; Geitz et al., 2015). However, according to other research teams, there was no relationship between PApG and the two levels of learning strategies (Elliot, 1999).

Methodology

Participants

This study was conducted on working students who were actively studying at a private university in Yogyakarta, Indonesia. The sample selection was carried out using a purposive sampling technique for six months. Moreover, the respondents were students who had been studying for at least two years and had worked for at least one year. This was because they are evaluated in the first two years for eligibility to be able to continue lecturing or not and also choose the field of specialization, and has status as a permanent employee. The specialization reflects the students' motivation and the strategies they choose to complete college. In this study, 506 students participated as respondents from 1000 students who were given questionnaires (response rate = 50.6%). The number was determined based on multivariate criteria, which required a minimum number of respondents equal to five times the number of question items used in this study. The questionnaires contained 30 items, therefore, the minimum sample was 150 people. In addition, confirmatory factor analysis was used as a tool to test the validity of the questionnaire. According to Hair et al. (2014), factor analysis requires a minimum of 300 respondents. Based on these considerations, 506 respondents were deemed sufficient to meet the requirements.

Measurement Scale

This study used a questionnaire adopted from Elliot and McGregor (2001) to measure the AGO dimensions and from Biggs et al. (2001) to measure two learning strategies. Meanwhile, a six-item questionnaire used in measuring SEBs was adopted from Kaplan and Maehr (1999). 5 items of MApG questions (for example, *It is important for me to understand this course material as completely as possible*, $\alpha = 0.866$), 5 items of PApG questions (for example, *It is important for me to perform better than other students,* $\alpha = 0.839$), and 4 items of PAvG questions out of 5 items used (for example, *I just want to avoid poor performance in class,* $\alpha = 0.722$) were valid and reliable. Meanwhile, for the learning strategy, 5 items of DLS questions (for example, *I spent a lot of free time discovering more about interesting topics that have been discussed in class,* $\alpha = 0.806$), and 5 items of SLS questions (for example, *I learned some things by repeatedly memorizing until I know it even though I don't understand it*, $\alpha = 0.702$) were valid and reliable. Finally, 6 SEBs items (for example, *even though the coursework is difficult, I can do it,* $\alpha = 0.838$).

Procedures

This study used primary data through a questionnaire distributed to students who were still active for at least two college years. The questionnaire utilized a five Likert Scale ranging from very disagree to strongly agree. A content validity test was conducted by asking an organizational behavior expert to evaluate the question items. Some students were also asked to read the questionnaires before distributing them to the respondents.

Furthermore, the construct validity was tested with confirmatory factor analysis (CFA) and reliability with the internal consistency of the questionnaire after obtaining the questions. The validity test was carried out using CFA with a loading factor of more than 0.5 or practically significant (Hair et al., 2014). Meanwhile, reliability testing using Cronbach Alpha was at least 0.7, as suggested by Hair et al. (2014). Correlation analysis was conducted to test the relationship between the two variables used in this study. A two-step approach in Structural equation modeling (SEM) using AMOS was used to test the four dimensions effect of AGO on two dimensions of learning strategies.

Results

Validity and Reliability Analysis

After testing the construct validity by factor analysis with a loading factor of more than 0.5 and reliability testing with a Cronbach Alpha of at least 0.7, subsequently, 14 of 16 question items used for AGO testing were declared valid and reliable. The loading factor ranged between 0.529 and 0.859. The five-question items in MApG had a loading factor from 0.624 to 0.856 and a Cronbach Alpha of 0.866. The five-question items in PApG gave a loading factor from 0.569 to 0.845 and Cronbach Alpha 0.839. The four-question items in PAvG had a loading factor from 0.529 to 0.807 and Cronbach Alpha 0.722. Meanwhile, the 10 question items used to test the learning strategies showed that all the items were declared valid and reliable. The loading factor for the ten items in question ranged from 0.601 to 0.805. The five-question items in DLS showed a loading factor from 0.615 to 0.805 and a Cronbach Alpha of 0.806. The five-question items in SLS gave a loading factor between 0.601 and 0.706 and Cronbach Alpha 0.702. Moreover, the six question items in self-efficacy beliefs showed a loading factor from 0.582 to 0.830 and a Cronbach Alpha of 0.818.

Descriptive Statistics

After the questionnaire was declared valid and reliable, correlation testing was conducted to examine the relationship between variables used and to test multi-collinearity between independent variables when the correlation between independent variables was more than 0.8. In addition, the mean was required to analyze the goals being pursued, the students' learning strategies, and the self-efficacy beliefs. Standard deviation was also needed to analyze deviations that may arise when the calculation is repeated. Descriptive statistics and correlation results are presented in Table 1.

Table 1. Mean, Standard Deviation, Reliability, Correlations between Variables

	1	2	3	4	5	6
PAvG (1)	1.000	0.312**	0.091*	0.053	0.426**	0.001
PApG (2)		1.000	0.495**	0.346**	0.156**	0.347**
MApG (3)			1.000	0.562**	- 0.044	0.423**
DLS (4)				1.000	- 0.067	0.503**
SLS (5)					1.000	- 0.154**
SEBs (6)						1.000
Mean	3.4570	3.6379	4.0040	3.5621	3.3004	3.7289
Std. Dev.	0.6638	0.6530	0.5960	0.5729	0.6021	0.6015
Cronbach's α	0.722	0.839	0.866	0.806	0.702	0.838

Notes: $^{**}p < 0.01$ level (2-tailed)
$^{*}p < 0.05$ level (2-tailed)

Table 1 showed that there was no correlation between the two learning strategies used by students. DLS was significantly and positively related to MApG as well as PApG and was not significantly related to PAvG. Meanwhile, SLS was significantly and positively related to PAvG and PApG. There was no correlation between SLS and MApG. The three dimensions of AGO were positively correlated, except between MApG and PavG. Furthermore, SEBs were positively correlated with PApG, MApG, as well as DLS, and were negatively correlated with SLS. Meanwhile, PavG was not significantly correlated with SEBs. The average DLS and SEBs were high (more than 3.67), while the other four variables were moderate (between 2.34 to 3.66). Moreover, all the variables in this study had a high standard deviation (more than 0.50), which indicated that the respondents independently filled out the questionnaire.

Simultaneous Model Testing Results

Based on the testing results, the three relationship models proposed in this study are shown in Figures 4, 5, and 6. The first model was not modified, but not all effects were significant. Meanwhile, the second and third models were modified according to the existing theory or data, and there were some insignificant effects.

Figure 4 shows the testing results of the first model, which indicated that DLS was positively affected by MApG and PApG, while SLS was positively affected by PAvG. This is consistent with previous studies (e.g., Diseth, 2011; Koopman et al., 2014; Zubkovic & Kolic-Vehovec, 2014).

Furthermore, DLS can increase SEBs, while SLS can reduce SEBs. This is consistent with previous studies (e.g., Garcia et al., 2016; McInerney et al., 2012; Ohrstedt & Lindfors, 2016). DLS that emphasizes understanding and experience, with an emphasis on critical thinking and knowledge, needs to be supported by the goals pursued by students, both the goal of mastering knowledge and demonstrating more abilities than others. Meanwhile, SLS is supported by the goal of students who do not want to appear less capable or less successful. This fear encourages students to use memorization strategies without understanding the material being studied. The first model test results were consistent with the previous studies that learning strategies mediate the relationship between motivation and perceived performance (e.g., Lin et al., 2017; Zhou & Wang, 2019). The positive effect of DLS and the negative effect of SLS on perceived performance also confirmed previous results (e.g., Chen et al., 2015; Everaert et al., 2017; Garcia et al., 2016; Murayama et al., 2013; Shearer et al., 2015; Zheng et al., 2018).

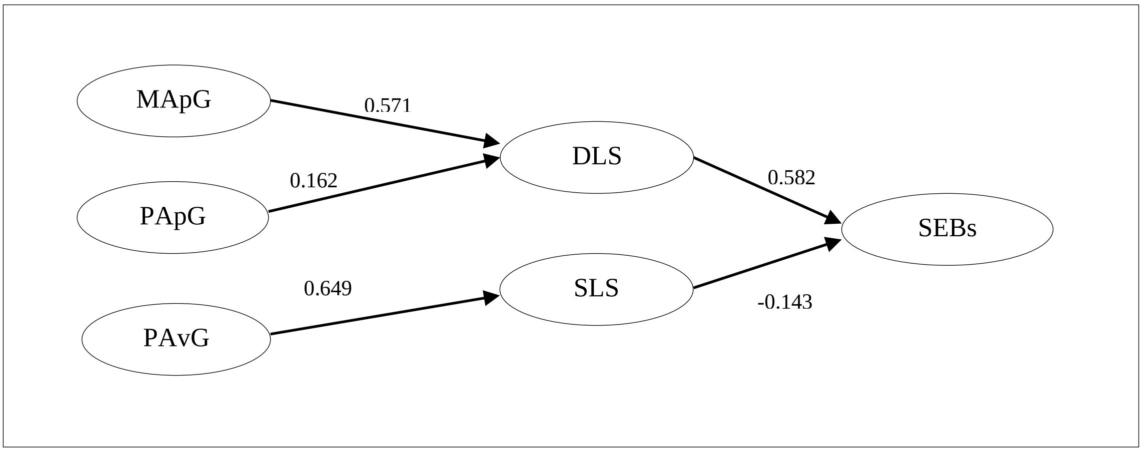

Figure 4. The First Model Testing Results: Learning Strategies Mediate the Effect of Achievement Goals on Academic Self-Efficacy Beliefs

According to the second model testing, some modifications were supported by theory and matched the existing data. The second model discovered a direct effect of MApG on DLS and PAvG on SLS. The modification results are presented in Figure 5.

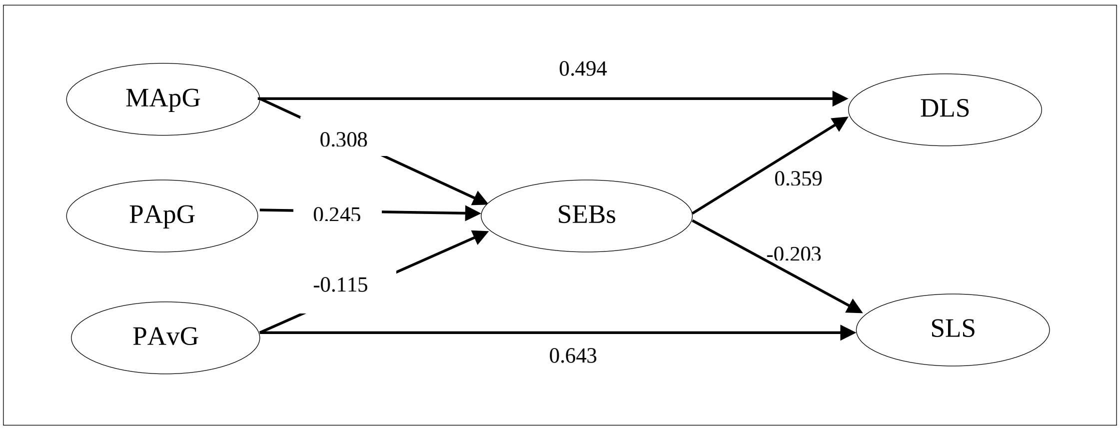

Figure 5. The Second Model Testing Results: Self-Efficacy Beliefs Mediate the Effect of Achievement Goals on Learning Strategies

Figure 5 shows that approach goals positively influenced SEBs, while avoidance goals had a negative effect. The testing results of this model were consistent with previous studies (e.g., Mason et al., 2013; Soylu et al., 2017; Turner et al., 2021; Zafarmand et al., 2014). High or low SEBs were influenced by the goals to be achieved. Generally, approach goals can increase confidence that is capable of obtaining certain achievements. Meanwhile, avoidance goals will reduce SEBs. SEBs positively influenced DLS and had a negative effect on SLS. High SEBs encourage individuals to choose learning strategies that prioritize material deepening, while individuals with low SEBs tend to memorize material without understanding it properly (Geitz et al., 2016; Shen et al., 2016; Kulakow, 2020). Furthermore, MApG and PAvG affected DLS and SLS, respectively. The direct influence of achievement goals on this learning strategy was consistent with previous studies (e.g., Diseth, 2011; Koopman et al., 2014; Shyr et al., 2017; Zubkovic & Kolic-Vehovec, 2014).

The third model required the most modifications because there was no match between the theory and existing data. This can be seen in the modified index and the difference between the goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI). The third model modification results are presented in Figure 6.

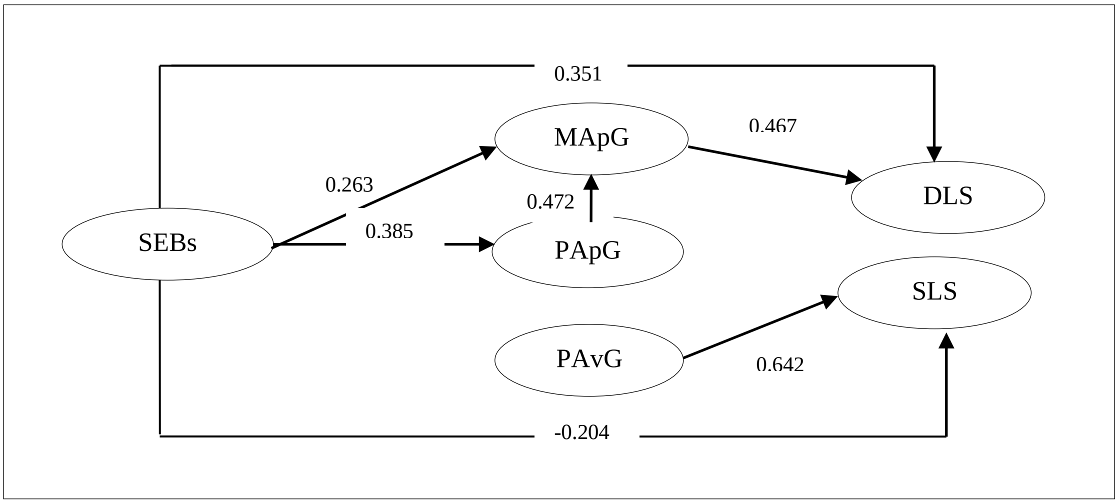

Figure 6. Third Model Testing Results: Achievement Goals Mediate the Effect of Academic self-Efficacy Beliefs on Learning Strategies

Figure 6 showed that SEBs only positively influenced approach goals and showed no effect on PAvG. Individuals with high SEBs will set higher goals, both to increase knowledge and to outperform their friends. This is consistent with previous studies by researchers (e.g., Azar, 2010; Bruning et al., 2013; Lee & Mao, 2016). MApG and SEBs consistently influence DLS. Meanwhile, PAvG consistently had a positive effect on SLS. The existence of a relationship or influence between SEBs, motivation, and learning strategies was consistent with previous studies. Besides being influenced by PAvG, SLS was also influenced by SEBs. SEBs decreased the use of learning strategies by memorizing. In this third model, PApG influenced MApG. In other words, the superior desire compared to others encourages individuals to increase their knowledge. This is in line with previous studies which reported that the combination of mastery and performance goals could motivate individuals more (e.g., Pantziara & Philippou, 2014; Senko et al., 2011; Wormington & Linnenbrink-Garcia, 2017).

Among the three relationship models based on the theory and previous studies, the model that most aligned with the theory and previous results or was most appropriate to the existing data was selected. As a comparison, various criteria were chosen. The comparison of the model's test results is presented in Table 2.

Table 2. Model Fit Index

	Chi-Square/DF	GFI	AGFI	CFI	RMR	RMSEA	NFI	IFI	TLI
Model 1	3.801	0.990	0.948	0.982	0.009	0.074	0.977	0.983	0.934
Model 2	0.342	0.999	0.999	0.999	0.021	0.001	0.997	0.999	0.999
Model 3	17.938	0.977	0.818	0.950	0.015	0.102	0.942	0.951	0.875

CFI = Comparative Fit Index
RMR = Root Mean-square Residual
RMSEA = Root Mean Square Error of Approximation
NFI = Normed Fit Index
IFI = Incremental Fit Index
TLI = Tucker-Lewis Index

The model testing results showed that the three models were in accordance with the theory and data based on absolute fit indices criteria (GFI > 0.95, AGFI > 0.95, RMR < 0.08, according to Hooper et al., 2008 suggestion). However, based on Chi-square/DF criteria as proposed by Hooper et al. (2008), the second model which had the smallest Chi-square/DF value, was the best. Likewise, with the criteria for RMSEA < 0.07, only the second model met the absolute suitability requirement (Steiger, 2007). However, based on the criteria for NFI > 0.95, comparative fit index or CFI > 0.95, and TLI > 0.95, as suggested by Hooper et al. (2008), the third model did not meet the NFI requirements. Therefore, the second model was the best as it met the requirements of conformity in SEM.

Strategy is almost always associated with culture and structure. Learning strategies are influenced by learning culture, which is also related to how learning is done (learning structures). In the context of Hofstede's cultural dimensions, learning culture is related to future uncertainty avoidance and long term orientation (Hofstede, 2011). This is often seen in the presence of stress, fatigue, anxiety, health and subjective well-being. Therefore, it is necessary to develop learning objectives that can generate self-confidence that individuals are able to achieve goals through appropriate learning strategies. Related to the focus on the long term, learning strategies must be adapted to the environment. Success is due to the right strategy and failure is caused by mistakes in formulating strategies.

Conclusion

Although MGO and PGO are mutually exclusive dimensions, this study indicated that they were correlated, although not all of them. Some students can be high in one dimension and low in another, while there are students who are high in both. According to the results, MApG positively influenced DLS but consistently had a negative effect on SLS. Competency development combination, mastery of new material, demonstrating competence, and obtaining positive assessments from others influence students' efforts to understand what is learned, understand or work with learning concepts and ideas without memorizing learning material. MApG is an achievement goal orientation dimension that directly or indirectly influences DLS through SEBs. Likewise, PAvG consistently increased the use of SLS as it was chosen by individuals with low self-efficacy beliefs.

Achievement goals, learning strategies, and self-efficacy are indeed three variables that influence each other. Each of them can be an antecedent and a consequence. However, the most appropriate relationship model with existing theory and data is that achievement goals affect the determination of learning strategies mediated by SEBs. Learning strategies which are performance predictors, were proven to be influenced by self-efficacy and achievement goals. Students' goals, SEBs, and learning strategies are three important factors that influence each other in improving performance.

This study provided several contributions. By paying attention to MGO learning strategies, teachers can provide challenging assignments, help students discover new skills, control the learning process or make decisions about it. Moreover, they help students to develop MApG, support the use of higher-order strategies, and enhance their learning. Goals are most effective when consistent or in context. PGO becomes adaptive when applied to educational contexts. The influence of MGO and PGO varies depending on the context. Therefore, future studies need to include social relations factors as independent or moderating variables.

This study had some limitations. Firstly, the data were obtained through self-report measurement at a time from several universities and grade levels, hence, there was a social desirability bias and a common method variance that can increase beta values. Furthermore, future studies need to separate the appraisers of independent and dependent variables from overcoming these problems. Secondly, this study could not make a causal explanation because it only looks at one moment for the variables. Therefore, a longitudinal study is needed to observe the causal relationship between the variables.

Acknowledgement

Special thanks to the respondents who participated in filling out my research questionnaire and thanks to the institutions that supported my research.

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RISK BASED APPROACH TO DOCUMENTING CONSUMER BEHAVIOR CHANGES DURING THE COVID-19 PANDEMIC

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Received: April, 2023
1st Revision: May, 2023
Accepted: June, 2023

ABSTRACT.
Background: People´s consumer behavior was significantly influenced by the Covid-19 pandemic. Nowadays, the impact still persists, and we can say that people changed the way how they think, shop, and what affects them while shopping. **Aims:** The aim of the article and our research is to identify and analyze the risks related to consumer behavior changes during the COVID-19 pandemic. **Methods:** To achieve the goal, survey research was conducted between the years 2021 and 2023 and, in use of SPSS Statistics, analyzed obtained data. To identify the representativeness of the sample file, the Chi-square test was used. Consequently, several contingency tables were created to analyze the set questions. **Sample:** The sample file consisted of Slovak consumers. **Results and Conclusions:** According to research findings, it can be concluded that the COVID-19 pandemic changed human thinking about such as common things like ways of shopping, consumption, or savings irretrievably. Implications: Overall, the COVID-19 pandemic created new challenges for both enterprises and consumers, however, many organizations managed to overcome them and adapt to continue to bring value to societies.

Keywords: consumer behavior, COVID-19, risks, sustainability, savings, consumption

JEL Classification*:* D12, D14, E21

DOI: 10.54933/jmbrp-2023-15-1-4

Veselovská, L., Hudáková, L. & Bartková, L. (2023). Risk based approach to documenting consumer behavior changes during the COVID-19 pandemic. Journal of Management and Business: Research and Practice, 15(1). doi: 10.54933/jmbrp-2023-15-1-4

Introduction

The COVID-19 pandemic emerged as a surprise, and its impacts are still resonating through societies worldwide. Many consumer behavior changes that occurred between 2020 and 2022 have already been well documented by many authors. The most complex findings can be found in the research of (Accenture, 2020; Vázquez-Martínez, Morales-Mediano & Leal Rodríguez, 2021; Valaskova, Durana & Adamko, 2021). A lot of attention has been given to exploring multiple ways how consumers changed their habits due to measures adopted by governments in order to mitigate the spread of the virus resulting in less frequent visits to shops. A paradox quickly became obvious that the more effective these measures were, the more negative impact they had on the business environment. Since the effects of the pandemic and these measures were immediate, companies were often able to respond quickly to new conditions and design strategies to mitigate the negative effects. Some companies were even able to use the pandemic as an opportunity to expand their business activities (Rychlik, 2020; Yan, 2020; Das et al, 2021). Nowadays, the COVID-19 pandemic is mostly over all around the world. However, what still is missing from the current pool of knowledge are the implications of the changes that occurred during the pandemic on long-term business activities and their future development. Therefore, this research focused on identifying and analyzing the risks related to consumer behavior changes during the COVID-19 pandemic considering not just the immediate effects but also the implications for the future in the form of long-term effects. Guidelines for the future can be derived from these results and their conclusions.

Theoretical background

The COVID-19 pandemic wreaked havoc in societies during years 2020 – 2022, with its effects still resonating strongly in 2023. This pandemic created unprecedented conditions even in the business environment that had no precedent in modern history. Moreover, businesses had to deal with not only the pandemic itself but also with restrictive measures imposed by governments to stop the spread of the virus. As the evidence from these troubled years shows, some businesses managed to implement changes and continue their operations. However, the majority of companies struggled (Chang et al, 2022).

Just as the environment changed, so did the people. The most evident examples can be found in alternations of consumer behavior. A consumer is a person who uses consumer products to satisfy his needs, wishes and desires, and expectations. Consumer behavior as a basic marketing variable is characterized as people's behavior related to the acquisition, use, and disposal of consumer products (Li et al, 2021). It is a summary of external manifestations, activities, actions, and reactions of the organism divided according to their psychological nature into instinctive, habitual, and rational (Valaskova et al, 2021; Khanna et al, 2022). Based on the understanding of consumer behavior, businesses can subsequently create their marketing offer and apply it to the market. Rushi & Pradhan (2023) described how the imposed measures and disruptions in supply chains led to product shortages that resulted in various cases of panic buying in many countries. The most obvious change was recorded in the frequency of visiting shops (Moharana & Pattanaik, 2022; Veselovská et al, 2022). Celik et al (2020) also describe the observed tendency of consumers to pay less attention to their expenses which can have major implications on the ratio between savings and expenditures in society. In many countries, at the beginning of 2021, negative phenomena such as excessive purchasing of products for stock or panic buying were observed (Omar et al, 2021; Lucker, Chopra & Seifert, 2021; Jin & Ryu, 2022). All these changes negatively impacted the business environment and threatened stability in societies.

Herve & Mullet (2009) and Stavkova et al (2008) described the factors that influence consumer behavior. However, during the pandemic, the influence of some factors diminished, and even new significant factors emerged (Gu et al, 2021). Due to forced social distancing, people were unable to connect with their friends and have face-to-face interactions. Home office measures also limited the contact between colleagues. As a result, the influence of these social groups decreased significantly (Veselovská et al, 2022; Sun et al, 2022) Furthermore, the influence of media and official government sources varied during the pandemic. People were more inclined to analyze the official information presented by the government carefully, and as consumers, they were influenced by them to act differently than they had before the pandemic. On the other hand, the popular media became less important when making decisions. According to Sun et al (2022) and Khanna et al (2022), during adverse events, people react more to official information provided by an authority more than during situations perceived as normal. Various authors also describe the phenomenon of people seeking more information during such times. However, they are more likely to trust the information provided by unreliable sources and hoaxes (Sun et al, 2022; Li et al, 2021). Many authors contribute that fear is a major factor in media coverage of pandemic-related stories and risk examinations (Rajkumar, 2022; Chen et al., 2022; He and Hu, 2022). Currently, there is little evidence of how this tendency affected purchasing decisions. Ali et al. (2022) discovered that internal and external factors such as rumors, government strategies, fear and anxiety, and health security significantly affect consumers' panic buying behaviors. These findings also related panic buying with internal and external consequences that affected all consumers, such as price hikes, shortage of supply of products, dissatisfaction of consumers, and increase in utility (benefit) of the products but not on consumer's budget. All these negative feelings can influence consumers to spend more money on buying goods than they need or even can afford. Therefore, the focus of information analysis also needs to be on changes in the consumption-savings ratio that can also negatively impact other aspects of the economy through bank systems.

Initial information indicates major changes in consumer behavior, the effects of which persist even in 2023, when the impact of the pandemic has significantly decreased. Many authors raised the question of how these consequences will affect humanity's intention to achieve sustainable development for a better future (Peterson et al, 2021; de Leaniz & Castro-Gonzalez, 2023; Škerháková, Harničárová & Tirpák, 2021). It is clear that many activities in the field of sustainable development have stopped or slowed down during the pandemic. Various authors (Zhang & Chang, 2021; Yu, Legendre & Ma, 2021) warn that risks to achieving sustainability have become more significant, and need strategies need to be adopted to incorporate the effects of the pandemic. However, it is still not clear exactly how the changes in consumer behavior contributed to such negative outcomes.

Any major variations in consumer behavior can significantly influence the business environment of any society. Even short-term disruptions can create a ripple that affects companies for many years. However, it is the long-term changes in consumer behavior that represent risks not only to private companies providing goods and services but also to any organization and even public institution. These risks come with both minor and major implications for societal impacts. Therefore, they need to be carefully identified and analyzed in detail in order to design measures to mitigate their negative effects or to utilize their potential to create new opportunities for growth in a sustainable environment.

Methodology

The consumer behavior changes documentation began as a part of a research project in 2021 when the data collection was initiated. The methodological approach selected for this study was empirical research. A survey was conducted in 2021 - 2023 in order to analyze changes in consumer behavior related to the pandemic of COVID-19 disease. The questionnaire was created and distributed among consumers for this purpose which consisted of 14 closed and semi-closed questions that collected data on consumer behavior changes and 5 closed questions aimed to provide consumers' socio-economic characteristics such as age, gender, level of education, household structure, and level of income. Empirical research was selected as the main research method to collect primary data since the data needed to sufficiently describe the changes in consumer behavior needed to include opinions of consumers on specific matters that are not yet available in any public databases of statistical bureaus. Therefore, a national survey was conducted on a representative sample of people in the Slovak Republic. Several stages of the survey were conducted to analyze the opinions and experiences of consumers in the Slovak Republic and then to compare them with international consumers. A questionnaire was used to evaluate the responses and to develop a comprehensive set of risks that threatens societies during the pandemic. The aim was to enable the use of findings as guidelines for the future. During the survey, the data was collected electronically using a questionnaire in Slovak language. The potential respondents were approached through selected partner consumer organizations, university students, and senior university organizations in order to achieve the largest data collection. All collected questionnaires were checked by members of the research team. Incomplete or inconsistent ones were discarded and not used further. Figure 1 presents the final structure of the sample file and information on how it related to the base file, which consisted of all Slovak citizens older than 18 years.

To ensure the representativeness of our sample files, we used Chi-square tests according to the criterion of the consumer's age. For each year, we have formulated null (H_0 – sample file is representative) and alternative hypothesis (H_1 -sample file is not representative). Statistic testing was performed in SPSS software. The Chi-square test of representativeness in this research was performed at a significance level of 95 % (α=0.05), which means if the p-values are lower than the selected alpha, the null hypothesis is rejected, and the sample file is not representative. In every year, the p-value was higher than 0.05, which means we cannot reject the null hypothesis, and our sample files are representative. To identify the frequencies of analyzed factors, contingency tables were used.

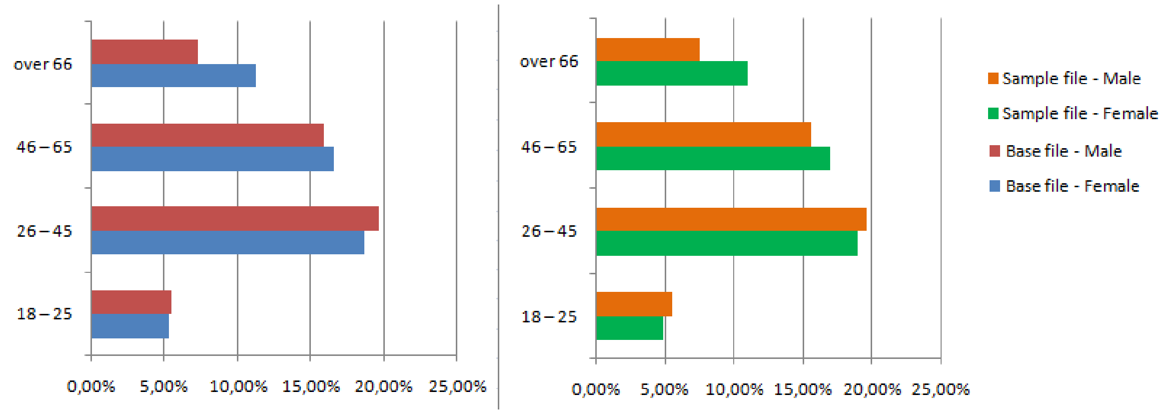

Figure 1. Structure of sample file based on age and gender of consumers
Source: *own data*

Results

The main aim of this research was related to risks that have the potential to significantly affect the business environment. Since the data collected for this purpose was from the Slovak Republic, the risks greatly map the environment and situation of this economy. A list of 24 risks was created. These risks were evaluated as those with a major impact on the business environment because they were related to significant consumer behavior changes. The full list is available upon request from the authors. Table 1 provides detailed information on 6 risks that were evaluated as the most significant in terms of the extent of their impact, the duration of their effect during the entire period of the COVID-19 pandemic, and the degree of impact on the business environment and overall life in society. Both the immediate effects of the risks and long-term effects were considered and also necessary for the creation of guidelines.

Table 1. Risks related to consumer behavior changes

Risk	Immediate effects	Long-term effects
increase in the number of products bought	panic buying SC disruptions increase in waste	threat to sustainability – sustainable consumption vs. sustainable production
changes in savings	changes in bank operations	instability of the monetary system and inflation
substitution of products (brand switching)	SC disruptions	worsening in the predictability of demand threat to sustainable consumption
stockpiling	product shortages increase in waste	worsening in the predictability of demand threat to sustainable consumption
emergence of new factors influencing consumer behavior	immediate need to respond to new factors	need to develop new marketing strategies
new forms of product distribution preference	technological changes and increased demand	necessary development of new sales strategies

The first major risk was related to the number of products consumers bought for their households during the period of the COVID-19 pandemic. The data shows that in 2021 the majority of consumers bought the same amount of products as before the pandemic. The situation changed dramatically in 2022 and 2023, when 51.7 % (2021) and 50% (2023) of consumers claimed a reduction in purchase volumes. Table 2 shows changes in the number of products (in %) consumers bought for their household through the years 2021, 2022, and 2023.

Table 2. Amount of products bought for households

	2021	2022	2023
I bought less	35,1	51,7	50,0
I bought more	18,2	14,8	12,5
I bought the same amount	46,8	33,5	37,5

The disposable household income can be divided into two categories: consumption and savings. The ratio of how consumers distributed their income changed significantly during the pandemic. Table 3 shows that in 2021 consumers mainly spent 50-70% of their incomes on the purchase of goods and services, which confirms the panic buying of consumers in that year. After the situation calmed down (years 2022 and 2023), the purchases came back to pre-pandemic levels, and consumers usually spend 31-50% of their incomes to purchase goods and services.

Table 3. Amount of income spent on the purchase of goods and services

	2021	2022	2023
Up to 10%	0	3,4	3,9
11 – 30 %	0	21,6	26,0
31 – 50%	37,5	33,0	29,9
51 – 70%	50,0	31,8	27,3
71 – 90%	12,5	9,1	9,1
91 and more %	0	1,1	3,9

Many consumers also decided to change the brands of products they usually buy due to various reasons. This research explored the extent to which these changes occurred and also the reasons for them. The data shows that 58.3% of consumers substituted the products they had bought before the pandemic for others in 2021. This rate of substitution increased in 2022 by almost 14%. The main reasons for the substitutions were availability, quality, and other personal reasons.

As documented examples from other authors show, stockpiling is often an accompanying sign of any major event. The COVID-19 pandemic also brought this phenomenon on, however, to differing extant in different stages of the pandemic. Up to 54% of consumers reported an increase in the amount of products they bought in 2021. This trend also continued in year 2022, which claimed almost 52% of consumers. However, this number significantly changed in 2023. This year only one third of consumers claimed that.

The influence of traditional factors affecting consumer behavior changed during the COVID-19 pandemic. Only less than 30% of consumers were influenced by media during the years 2021 -2022. Furthermore, new factors of influence emerged, such as a feeling of safety in shops and accessibility of shops. Table 4 shows all factors that influence consumers´ decision to purchase a product or service during the pandemic with the percentage of consumers.

Table 4. Factors affecting consumer behavior

Factor	Percentage
Family	45,6
Expert information	42,8
Previous experience	46,2
Feeling of safety in the store	47,5
Store location	40,7
Shop availability	41,3

One of the most obvious outcomes of the pandemic was the increased need for new forms of product distribution. The online shopping with home delivery became especially significant in 2022. Even the food delivery increased during the pandemic. Figure 2 presents the corresponding data. Clearly, the increase in delivery was observed in the age group of 31 – 50 years. Moreover, these trends remained active even in 2023. These findings indicate a potential new trend in product distribution.

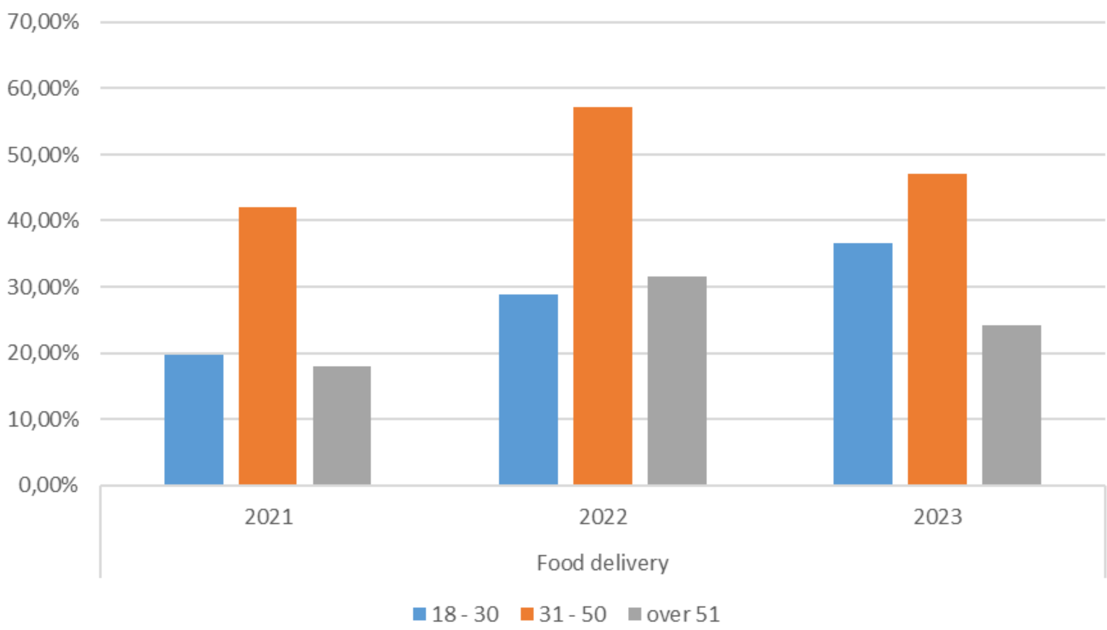

Figure 2. Food delivery utilization based on age and year of the pandemic
Source: *own data*

Conclusion

It is now clear that the pandemic severely and, in some cases, even irreversibly altered modern-day life in societies. The long-term implications are not yet obvious, however, the immediate effects of what the COVID-19 pandemic left us with are clear. The first and most important factor that all consumer behavior change-related research focused on was possible changes in the number of goods and services purchased. This assumption of changes has been confirmed in all countries in the world, but not to the same extent. A positive trend was observed in some states (Guney & Sangun, 2021), but in most states, consumers increased the amount purchased (Basu & Swaminathan, 2021). In the Slovak Republic, up to 67.2% of consumers younger than 35 years increased the number of products they bought in 2021, but in 2022 only 20.3% of these consumers did this. It is necessary to evaluate this factor from a time point of view. Other changes were noted at the beginning of the pandemic in 2021, and differently, consumers approached the amount purchased in later periods of the pandemic. In many countries, at the beginning of 2021, negative phenomena such as excessive purchasing of products for stock or panic buying were observed (Omar et al, 2021; Lucker, Chopra & Seifert, 2021;

Jin & Ryu, 2022). The results of the primary survey confirm that both of these phenomena pose significant risks.

Since the COVID-19 pandemic significantly altered the shopping habits of consumers, many entrepreneurs had to make changes to their day-to-day operations in order to survive. However, survival is the fundamental goal; it should not be the main reason for existence. All businesses aim to strive, and for that, they need successful business strategies. The findings of this research provide them with guidelines to define their strategic goals and means to flexibly adjust them when the next pandemic arises in the frame of sustainable development. One of the main findings includes the fact that modern consumers pay very little attention to savings. This risk was evaluated as significant not only because of the pandemic but also in relation to rising inflation as an accompanying phenomenon of the economic crisis. Up to 66.7% of younger consumers used 70% or more of their household income for buying products and services during the pandemic leaving only a minor part of their income for savings during the pandemic. There were no significant alterations in consumption – savings distribution of consumers' income during different stages of the COVID-19 pandemic. These findings indicate a fundamental risk for people in society who, with a low orientation towards creating savings, may become insolvent in the near future. As a whole, the lack of savings creates problems in the banking sector as well, which in the long run, can lead to such high inflation that would even further impair people's ability to satisfy their needs by purchasing goods and services.

Furthermore, many sectors of the economy experienced supply chain disruption during the pandemic (Sarkis et al, 2020; Khan et al, 2022). Although the main cause was the lockdowns and production slowdown, many consumers also changed their preferences during the pandemic, which resulted in the substitution of products for other brands. Although the majority of consumers indicated that the reason for substitution was the price of the product (56.4%), up to 33.9% of consumers indicated insufficient quality as the reason for the change. Although, at first glance, this is a negligible share of consumers, it is necessary to state that this share was higher in 2022 than in 2021, indicating an upward trend. It is thus possible to deduce that during the pandemic, consumers paid more attention to the ratio of price and quality of the product. In the future, the demands on the quality of products will increase, which is what manufacturers should focus on not only in the product itself but also in the promotion of the products. Furthermore, current research indicates that consumers are becoming increasingly more socially conscious (Zulauf, Cechella & Wagner, 2021; Zhang, Chen & Grunert, 2022). The obvious implication of these findings is related to new challenges for marketing campaigns. The need to expand the orientation from corporate social responsibility to sustainable consumption and production patterns will become a necessity for all modern enterprises, with the focus of their propagation activities on motivating consumers to save more and buy only what they really need, which is quite a shift in thinking inherited from consumption-oriented societies of 20th century.

Since the impacts of the pandemic on sustainability were mostly negative (Zhang & Chang, 2021; Yu, Legendre & Ma, 2021), it is clear that risks that threaten these aspects of human life have emerged. The measures adopted by governments to stop the spread of the virus resulted in an increase in stockpiling of goods, as reported by 41.5% of consumers. An increase in consumption and stockpiling often resulted in throwing food away, which led to an increase in produced waste. The specific category was plastic waste which generation also increased, especially in the food sector since many restaurants were partially closed, allowing only take-out or delivery. The distribution needed to be adopted during the pandemic. This is most likely the change that will persist even after the pandemic is completely eradicated. The technological changes required to accommodate these new needs are already in place and will continue to evolve rapidly. However, this will require businesses to adjust, discovering new factors that influenced consumers during the pandemic. The omnipresent risk of infection caused up to 87% of consumers to be sensitive to the feeling of safety while shopping and 62% of customers also chose a store based on its location. The emergence of these new factors influencing consumer behavior, such as safety in shops and shop location and accessibility, will play a key role in the future and should be used in targeted marketing campaigns.

The main limitation of this study could be considered its sample file since it consisted solely of consumers from one country that may not be the representative example of its region or the world. However, the findings of this study represented by the set of risks could be applied to any country if carefully compared to its national consumer behavior indicators. There also lies the potential for future research since, overall, the COVID-19 pandemic created new challenges for both enterprises and consumers, however, many organizations managed to overcome them and adapt to continue to bring value to societies. However, the long-term effects of the COVID-19 pandemic remain uncertain and need to be carefully monitored.

Acknowledgment

This contribution was supported by project No. 1/0134/22, "Changes in consumer behavior due to the COVID-19 pandemic with intent to predict its development".

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PROCESSUAL BENEFITS OF PREDICTIVE MAINTENANCE IN THE MIDMARKET

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Received: Mach, 2023
1st Revision: June, 2023
Accepted: June, 2023

ABSTRACT.
Background: Industrialization has given rise to numerous new topics for companies. In the age of Industry 4.0, predictive maintenance represents an opportunity to reduce machines' downtime and enable companies to gain competitive advantages. For this purpose, sensors are installed in machines, and the data of individual parts is constantly monitored and evaluated. By detecting possible failure risks of individual parts at an early stage, they can be replaced before the downtime occurs, thus preventing a long downtime. A shorter downtime can bring further positive aspects in multiple terms. A lot is written in the literature about the general advantages of predictive maintenance, but there is no particular focus on the German midmarket sector. **Aims:** The aim of this paper is to find out how midsize companies perceive the processual benefits of predictive maintenance. **Methods:** A standardized questionnaire with four questions is developed. **Sample:** Answers from 104 respondents are evaluated. **Results:** The results show that a large proportion of the respondents expect added value. **Conclusion and Implications:** The research in this paper shows that the added value generated by predictive maintenance is not limited to multinational corporations but can also be realized in medium-sized companies.

Keywords: *Industry 4.0, Internet of Things, Predictive Maintenance, Value Generation*

JEL Classification*:* M20

DOI: 10.54933/jmbrp-2022-15-1-5

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Introduction

Digitization in Germany is advancing rapidly, and the Corona pandemic, in particular, has given companies in Germany a boost in their progress toward digitization. However, there is still a considerable need for German midsize companies to catch up in some areas of digitization (Neuerer, 2021). Predictive maintenance is considered one of the drivers of digitization and is the subject of considerable discussion. The goal of predictive maintenance is to prevent machine failures and thus save costs. The subject of predictive maintenance was only made possible by the transformation of the industry from Industry 1.0 to Industry 4.0 and modern technologies (Haarman et al., 2017).

However, predictive maintenance also poses a number of challenges that need to be considered in greater detail during implementation. On the one hand, the technical prerequisites for monitoring machine data must be in place, and on the other hand, contractual and legal framework conditions must also be taken into account during implementation. Even though studies on predictive maintenance show promising results, companies should always consider these scenarios on a case-by-case basis and work out the appropriate implementation methodology (Roland Berger GmbH, 2017). Modern topics such as machine learning are also being combined with predictive maintenance to achieve benefits through less frequent machine downtime and improve the prediction accuracy of the algorithms (Tessaro et al., 2020).

There is a current research gap in this field, as the studies mainly focus on large enterprises rather than specifically in the German midmarket. To this end, the theoretical background and the current state of research will first be presented, followed by an explanation of the research methodology. The data basis for this measurement will be companies from German medium-sized businesses from various industries. It is important to highlight that this study‘s results are to be validated for other countries to ensure the maximum added value for international companies.

Theoretical background

Industry and production have existed for many centuries. For modern industry, however, there are mainly four relevant revolutions which have changed the way of working decisively. While in the beginning, the focus was still strongly on physical machines, the 21st century has brought data and the networking of machines to the fore (Becker et al., 2017). The following figure shows the development of the four industrial revolutions.

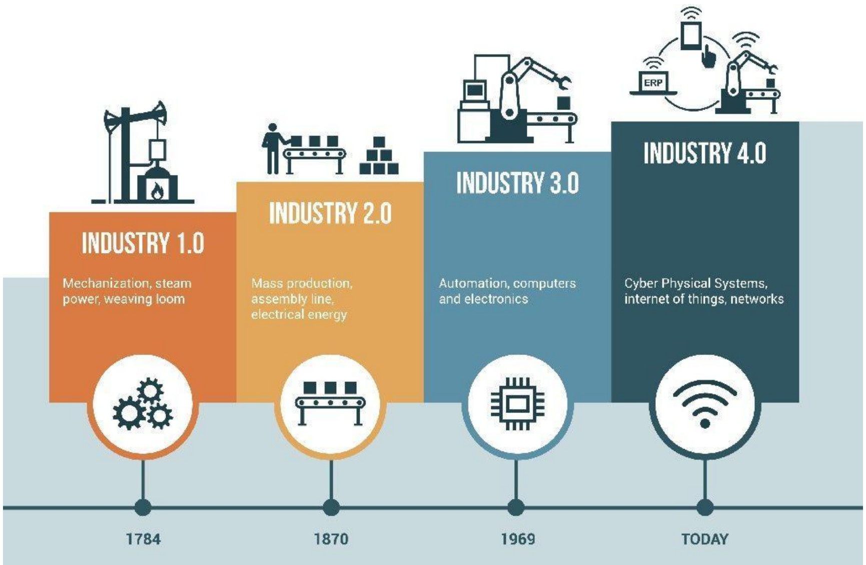

Fig. 1 – From Industry 1.0 to Industry 4.0. Source: Diaonescu, 2018

This figure shows the key points of the respective steps between Industry 1.0 and Industry 4.0. Due to the scope of this paper, the most important key points considered as fundamentals for the current application of predictive maintenance will be explained hereafter.

The mechanization and steam-powered machines were particularly important for Industry 1.0. Through them, it was possible to increase productivity enormously and generate greater output than was the case with manual activities (Bauernhansl, 2014, p. 5). The first steam-powered loom is seen as a key innovation for the textile, steel and iron industries (Siepmann & Graef, 2016, p. 19).

The second industrial revolution was characterized by the use of electrical energy and the associated mass production based on the division of labor. The assembly line developed by Henry Ford enabled workers to specialize in individual work steps and to achieve higher productivity through the division of labor. Frederic W. Taylor's work on scientific management also helped to restructure companies. With the development and use of combustion engines, petroleum became increasingly important as a fuel for mobile systems. Machines could now be operated decentrally, and automobiles became part of logistics. The developments of Industry 2.0 were signposts for today's consumer-oriented affluent society. The further development of automobile traffic, the use of airplanes and the possibility of long-distance transportation by ship made increasing globalization possible (Bauernhansl, 2014, pp. 6–13).

The third industrial revolution was triggered by the development and use of electronics and information technology. Based on the developments of Lovelace and Babbage from the first industrial revolution, Konrad Zuse developed the world's first functional computer in 1941 (Frick, 2017). It enabled progressive automation of production processes, which was one of the reasons for the economic miracle in Germany at that time. The use of information and communication technology led to rationalization, but it also enabled a varied series of production (Bauernhansl, 2014, p. 7).

The German working group Platform Industry 4.0, consisting of the associations Bundesverband Informationswirtschaft, Telekommunikation und neue Medien, Verband Deutscher Maschinen und Anlagenbau and Zentralverband Elektrotechnik- und Elektronikindustrie, focuses in its definition of Industry 4.0 on the control of the value chain over the product life cycle, which is only possible through the availability of real-time data. This working group is an association of various German industrial societies which publish recommendations and information for German and international industries. The main goal is to support companies' progress and make modern, often not widely used technologies more tangible. They define Industry 4.0 as a term that stands for the fourth industrial revolution, a new level of organization and control of the entire value chain over the life cycle of products. This cycle is oriented towards increasingly individualized customer requirements and extends from the idea, the order, through development and production, the delivery of a product to the end customer, to recycling, including the associated services. The basis for this cycle is the availability of all relevant information in real-time through networking of all instances involved in the value chain and the ability to derive the optimal value chain flow at any given time from the data. By connecting people, objects and systems, dynamic, real-time-optimized and self-organizing, cross-company value-added networks are created, which can be optimized according to various criteria such as costs, availability and resource consumption (Plattform Industrie 4.0, 2015, p. 8).

Now that the basics of industrial change have been described as a prerequisite for predictive maintenance, the topic of maintenance will be discussed in more detail next. While machine maintenance is about reducing or preventing wear and tear, repair aims to eliminate the wear and tear that has occurred. A typical repair procedure includes the decommissioning of the affected plant, decoupling it from the surrounding plant, dismantling and cleaning, damage detection, replacement or repair of the affected parts, including adjustment and adjustment of the assembly as well as functional testing and recommissioning (Hölbfer, 2014, p. 16). According to Aha, there are three different maintenance strategies in which the basic measures just mentioned are implemented. There belong the failure-related maintenance strategy, the planned preventive maintenance strategy and the condition-based maintenance strategy (Aha, 2013, pp. 19–20). Predictive maintenance is a core component of Industry 4.0 and clearly distinguishes itself from conventional maintenance approaches such as reactive or preventive maintenance. This involves installing sensors on the individual parts of a machine and monitoring whether they run faster, are noisier or get hotter than expected, for example. This data is then used to calculate the probability of a part or machine failing within a given time frame. Recognizing these patterns makes it possible to identify the faulty parts at an early stage. This can make a big difference to machine downtime, as parts that are needed can be ordered early, and production can be designed to accommodate repairs. It is necessary to collect, store and analyze a large amount of data to make reliable predictions for predictive maintenance. Due to the vast amount of data, techniques and databases from the big-data environment are used. The recorded measured values and diagnostic data are transmitted from the machines via networks to service centers or directly to the manufacturers. In many cases, the Internet of Things serves as the network technology basis (Carvalho et al., 2019). Two major challenges in the technical implementation of predictive maintenance that companies can face are the quality and quantity of the data. A distinction is made between the required data, i.e. the data that would not be possible without predictive maintenance, and additional data that improves the quality of the predictions (Schleichert et al., 2017, p. 11).

In the literature, it has not been clearly worked out at which points medium-sized companies in Germany can benefit from predictive maintenance. Authors like Shamayleh et al. highlight the benefits for specific industries like medical companies but do not focus on the German midmarket in a cross-industry approach (Shamayleh et al., 2020). In the following, therefore, a method will be presented that is intended to make this consideration possible by using a questionnaire and conducting quantitative research.

Methodology

By using a standardized questionnaire, results are to be obtained on four questions in the subject area benefits through predictive maintenance. The target group for the survey is defined as:

- Midmarket companies based in Germany. Since there is no universal definition for the term midmarket, a company size of up to 500 million euros in annual company turnover is taken as the basis for the following research
- No pre-selection based on age, gender or position in the company

To formulate the questions, a structure tree has been developed for operationalization by means of a dimension analysis. For this purpose, the construct is defined as "added value through predictive maintenance". The dimension this research focuses on is the processual dimension. Therefore, the following indicators are used:

- Maintenance duration: How long does it take to check or repair a machine?
- Duration of downtime: How long does it take a machine to stop if a part is defective?
- Lifetime of the machines: How long is a machine in use on average from the time of purchase to the time of disposal?
- Frequency of maintenance: How often do machines need to be maintained during their life cycle?
- The following questions or statements were then developed to assess the impact of predictive maintenance at the subjects' companies:
- The use of predictive maintenance would reduce the time needed to maintain our machines.
- The use of predictive maintenance would reduce the time our machines are out of operation due to maintenance or a defect.
- The life cycle of our machines would be extended by using of predictive maintenance.
- Our machines would require less frequent maintenance by using predictive maintenance.

Due to the questionnaire design, primarily closed questions are asked. Mainly a verbalized ordinal scale is used to answer the question with the possibility to assign 1-5 points with the meaning "Do not agree at all", "Do rather not agree", "Neither agree nor disagree", "Do rather agree" and "Agree completely". Additionally, there is the possibility to skip the question with the answer "No answer". This answer option can be selected if there is either no opinion on the statement or the respondent does not want to rate the statement.

The questionnaire is sent electronically via Google Forms to 192 subjects, of whom 104 participated in the survey, a rate of approximately 54%. The data is collected electronically via Google Forms. The subjects are contacted personally, but the responses are evaluated anonymously. The survey is completed using Google Forms. This ensures that the respondent's name is not requested and that no correlation can be made on the basis of other criteria.

Cronbach's alpha is used to check reliability. This measures the degree of correlation between several questions within the questionnaire in order to ensure internal consistency. Values below 0.5 are regularly considered unacceptable in science and indicate that the individual items of the questionnaire should be reviewed.

In order to check the comprehensibility and meaningfulness of the questions, a pretest was carried out in advance of the survey. For this purpose, two experts from the industry were interviewed, followed by a test subject with whom the comprehensibility of the questions was discussed. After completion of the pretest, no changes were made to the questions.

Results

104 respondents took part in the survey, and none of the answers were invalid or missing.
The following answers were given to the statement, "The use of predictive maintenance would reduce the time needed to maintain our machines":

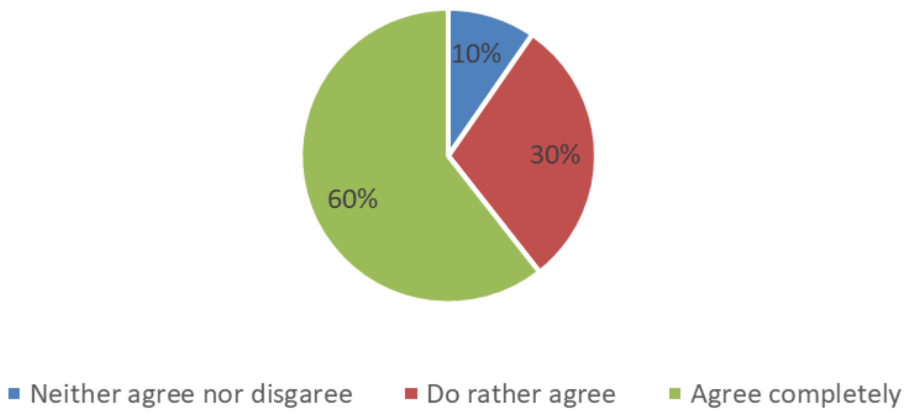

Figure 2: Pie Chart for Question 1. Source: Own research

The following answers were given to the statement, "The use of predictive maintenance would reduce the time our machines are out of operation due to maintenance or a defect":

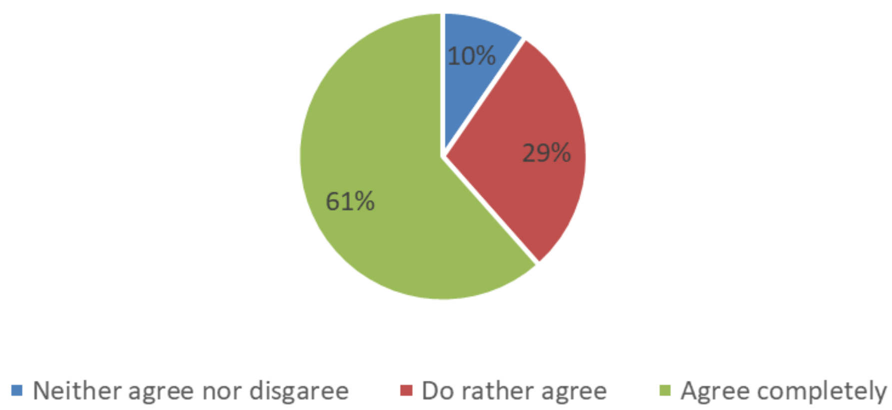

Figure 3: Pie Chart for Question 2. Source: Own research

The following answers were given to the statement “The life cycle of our machines would be extended by using predictive maintenance”:

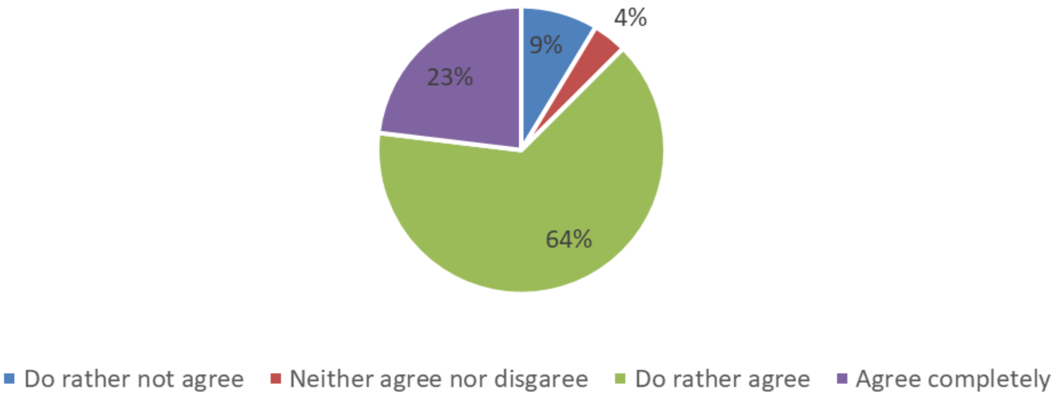

Figure 4: Pie Chart for Question 3. Source: Own research

The following answers were given to the statement “Our machines would require less frequent maintenance through using predictive maintenance”:

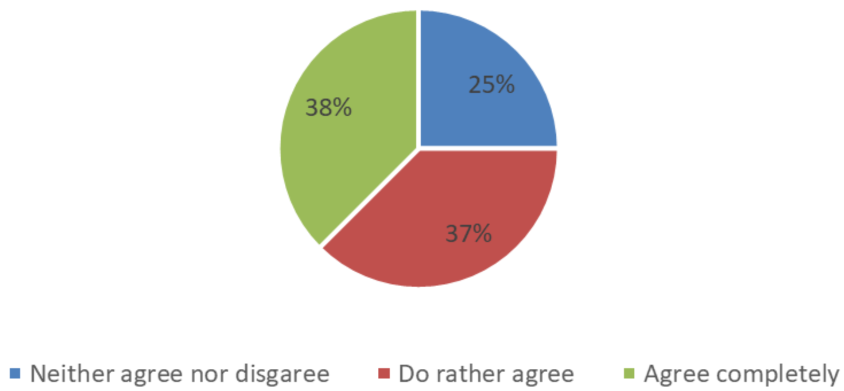

Figure 5: Pie Chart for Question 4. Source: Own research

If we consider the two categories "Do not agree at all” and "Do rather not agree" as perceptions of no added value, the category "Neither agree nor disagree" as neutral, and the two categories "Do rather agree" and "Agree completely" as perceptions of added value, the responses reveal a clear picture. Across all four questions, an average of 2,18% see no added value, 12% are neutral about predictive maintenance, and 85,82% see the added value.

Conclusion

The answers to each of the questions show that an added value of predictive maintenance is perceived by the majority of the respondents. This is consistent with the literature, which reports on the benefits and effects of predictive maintenance from a general point of view. The data collected in this study from 104 subjects came exclusively from companies belonging to the German midmarket. By combining the results of this study with the expected values through the literature research, it can be assumed that the present results can also be transferred to companies of other sizes or from other countries, provided that at least similar basic conditions exist. As identified in the literature review, there are certain prerequisites for the successful use of predictive maintenance, which can be found in the technical area, among others. Without these basic prerequisites, it is unlikely that the same added values can be achieved as expected by the subjects of this research study. For subsequent studies, it may be interesting to specify the results for the value-added consideration of predictive maintenance even more precisely regarding individual industries. It may also be interesting to validate the assumption of similar results through studies in other countries.

In the following, the three quality criteria, objectivity, reliability and validity, are considered. Objectivity is achieved by using a standardized questionnaire in combination with an anonymous survey. The results are, therefore not influenced by interpersonal interaction and should show the same results with another researcher. Reliability was calculated by Cronbach's Alpha and showed an acceptable result with a value of 0.70. Omitting individual items would not have significantly improved Cronbach's Alpha. Other methods, such as a retest or a parallel test, were not used due to the scope of this work. In terms of validity, content validity was ensured by pretesting with two experts in predictive maintenance. Construct validity was ensured by aligning and deriving the questions from the literature review.

Predictive maintenance is a topic that can generate a great deal of added value for many companies. Even though the topic has been discussed for several years, many companies have not yet used it. During this paper, the basic requirements for predictive maintenance and how the literature describes possible added values through predictive maintenance were worked out. Due to a research gap in the area of predictive maintenance in German medium-sized businesses, this paper took a closer look at this area. The majority of the 104 participating respondents see a potential added value in their company using predictive maintenance. For future research, it may be interesting to set an industry focus and to question how the added value through predictive maintenance is presented in individual sub-industries. The research results of this work can also be generalized to other countries and company sizes under similar basic conditions and are valid not only for the German midmarket.

The first applications and results of predictive maintenance are already being implemented and realized in the industry. However, the response to these possibilities is still very restrained, especially in German medium-sized companies, even though the possible results look promising. By increasing research in these areas, it may be possible to introduce more companies to predictive maintenance and convince them of the potential benefits. The research in this paper provides reliable starting points that can be elaborated in more detail in more in-depth research. Future research will show the international impact of predictive maintenance and the differences that may occur between different countries.

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