THE ROLE OF NEED FOR STRUCTURE IN TECHNICAL ANALYSIS AND HOW IDENTIFYING INFORMATION IN PRICE MOVEMENTS RAISES TRADERS' CONFIDENCE

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Abstract: *Technical analysis (TA) is a tool believed to support investor's investment decisions. Even if research has demonstrated that TA cannot be used to make systematic profits over a long time period, it could potentially bring psychological payoffs to its users in the form of enhancing their confidence. In an experimental study we show that: (1) chartists demonstrate overconfidence in TA usage, believing that they are better than they actually are in TA formation recognition, and that; (2) the act of naming an observed trend as a TA formation brings extra confidence to the chartist, regardless of whether this is a real TA sequence or a random sequence. Thus, both naming an existing TA formation as a TA formation and naming a random sequence as a TA formation result in greater confidence.*

Also, irrespective of the high popularity of TA among investors, there are marked individual differences in TA followers. In a questionnaire study, we demonstrate that declared positive attitudes toward TA correlate positively with

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high need for (cognitive) closure (as measured by the Need for Cognitive Closure Scale; NFCS), specifically, desire for predictability.

Key words: *technical analysis; chartists; overconfidence; confidence; dubious data; cognitive closure.*

POTRZEBA STRUKTURY W ANALIZIE TECHNICZNEJ. JAK IDENTYFIKOWANIE INFORMACJI W RUCHACH CEN ZWIĘKSZA ZAUFANIE TRADERÓW

Streszczenie: *Analiza techniczna (AT) to narzędzie, które ma wspierać decyzje inwestycyjne inwestora. Nawet jeśli badania wykazały, że AT nie przyczynia się znacząco do osiągania systematycznych zysków w dłuższym okresie, to może jednak przynosić korzyści psychologiczne dla użytkowników. W badaniu eksperymentalnym wykazaliśmy, że: (1) inwestorzy wykazują nadmierną pewność siebie w stosowaniu analizy technicznej, przeceniając swoje umiejętności w rozpoznawaniu płynących z niej sygnałów; (2) sam akt nazwania obserwowanego trendu „formacją AT" podnosi pewność inwestora wobec własnego sądu, niezależnie od tego, czy w rzeczywistości jest to prawdziwa sekwencja AT, czy też ciąg losowy. Zatem zarówno nazwanie istniejącej formacji AT jako „formacji AT", jak i nazwanie losowej sekwencji jako „formacji AT" skutkuje wzrostem pewności siebie inwestora.*

Niezależnie od wysokiej popularności AT wśród inwestorów, istnieją wyraźne indywidualne różnice pośród zwolenników AT. W badaniu kwestionariuszowym wykazaliśmy, że zadeklarowane pozytywne postawy wobec AT korelują dodatnio z wysoką potrzebą domknięcia poznawczego, w szczególności z preferowaniem przewidywalności.

Słowa kluczowe: *analiza techniczna, czartyści, nadmierna pewność siebie, pseudodane; potrzeba domknięcia poznawczego.*

INTRODUCTION

This paper examines the problem of using dubious information when decision making. This propensity can be observed in many situations. For example, patients often seek advice from various types of quack doctors despite the lack of proof of their medical competence. Also, many people buy various types of dietary supplements, despite the evidence for their effectiveness being limited to say the least. Perhaps most notoriously of all, in 1998 Andrew Wakefield and colleagues pub-

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lished a study based on an extremely small sample number ($N = 12$) of anecdotal cases suggesting a link between the MMR (measles, mumps, and rubella) vaccine and pervasive developmental disorder (autism) in children. Although it was later retracted, the paper, and the problematic data that it was based on, received wide publicity and influenced the vaccination decisions of many parents worldwide. Even retracting the paper did not provide an effective solution in countering the effects of the false information that it contained. This relates to the well-known task where a person is asked not to think about a pink elephant: once this instruction has been given, they cannot help but think of a pink elephant. Lawyers exploit this phenomenon in their practice, inadmissible evidence usually remaining influential with jurors once it is known to them – for more, see the review of such studies by Markiewicz and Markiewicz-Żuchowska (2012).

The current paper considers the use of dubious information in the context of making decisions involving financial markets. Several methods are used to support financial investment decisions: portfolio analysis, statistical analysis of historical market data, fundamental analysis, and technical analysis (TA). TA is a method of using historical market prices and volume analysis to support an investor's forecasts (Murphy, 1999). TA tools seek to take advantage of nonlinear features of trading systems by using TA indicators (see (Campbell, Lo, & MacKinlay, 1997; Lo, Mamaysky, & Wang, 2000). Although some studies provide evidence that selected TA methods have some limited effectiveness (for some asset classes and certain time periods, see e.g., Lo, Mamaysky, & Wang, 2000), there are many theoretical reasons to doubt TA's efficacy. For example, even according to the weak form of the efficient market hypothesis (EF. Fama & Blume, 1966), TA simply cannot be used to make systematic profits over a long period of time. The weak form of the efficient market hypothesis suggests that the current price of a security reflects all currently available information, including previous prices (EF Fama, 1970). Such skepticism regarding TA is justified, studies showing that its use is not profitable (Aronson, 2011; Hsu, Hsu, & Kuan, 2010; Kubińska, Czupryna, Markiewicz, & Czekaj, 2018). More specifically, the idea that TA can generate extra profits is often lacking in terms of statistically significant evidence, and, even where such evidence is presented, it can easily be explained by data mining bias or post factum analysis. But, in spite of the above doubts as to their efficacy, TA techniques still enjoy worldwide popularity among both professional and lay market participants (Lo & Hasanhodzic, 2009, 2010; Sturm, 2014) .

So, what causes this passion for TA when the evidence of its effectiveness is extremely limited at best? Several mechanisms have the potential to contribute to an explanation:

(1) Operant conditioning in an associative learning process modifies behavior by repeated reinforcement. When a rat in a Skinner box occasionally

obtains food by pressing a lever, its rate of pressing increases, and the (random) reinforcement that occurs after a variable number of responses typically yields a very persistent behavioral pattern. Similarly, a trader may experience positive reinforcement when obtaining a "random hit" in TA, this encouraging further use of an inefficient technique.

(2) Decision makers often pay selective attention to evidence favoring their expectations. Thus, they tend to favor information that confirms their preconceptions, and are not interested in information that could falsify them. Peter Wason coined the term "confirmation bias" to describe this cognitive bias, and Wojciszke (2009) suggested that this may provide a means of understanding decision makers' (DMs) propensities for using dubious data (pseudo-data). Thus, to test whether the idea that TA predicts future price movements holds, a DM should gather evidence for each possible type of situation (ABCD in Table 1).

Table 1
Evidence matrix for testing whether TA is effective

	Hypothesis	
Evidence	The observed chart represents a certain TA formation	The observed chart does not represent a certain TA formation
The price has moved in the direction signaled by the possible TA formation	A Data confirming the hypothesis	B Data disconfirming the hypothesis
The price has not moved in the direction signaled by the possible TA formation	C Data disconfirming the hypothesis	D Data confirming the hypothesis

A problem occurs when a DM is not equally interested in all the information (ABCD). A DM who favors TA (a chartist) may not treat data falling into the A and C categories equally: when they have a personal attachment to a hypothesis they may disregard evidence in category C (claiming the influence of some third factor, such as choice of incorrect time horizon or format of historic data presentation (Weber, Siebenmorgen, & Weber, 2005) or some possible perception problems (Weber, 2004) to protect the hypothesis they are attached to. Thus, the DM's belief in the hypothesis would be strictly proportional to their observations concerning category A evidence, information concerning category C being easily disregarded, superseded, or simply forgotten. In the present study, we hypothesized that category A observations build more self confidence in a chartist than category C observations, thus:

H1a: When chartists classify evidence as belonging to category A, they will be more confident in a decision compared to when they classify evidence as belonging to category C.

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Similarly, as chartists are more interested in testing their hypothesis (using evidence relating to A and C), than testing the alternative hypothesis (using evidence relating to B and D), it is reasonable to suggest that evidence concerning A and C will be more salient to them than that concerning B and D. Consequently, the first hypothesis a chartist should consider is that "the observed chart represents the TA formation", and only if no evidence is found should they go one step further to test the alternative hypothesis "the observed chart does not represent the TA formation". Thus, it is reasonable to suggest that cumulative category A and C evidence should build more self-confidence in a chartist than cumulative B and D observations. Furthermore, as chartists test an alternative hypothesis unwillingly and are highly attached to their main hypothesis, they should favor category B evidence over category D evidence. This reasoning suggests the following hypothesis:

H1b: When chartists classify evidence as belonging to category B, they will be more confident in a decision than when they classify evidence as belonging to category D.

In addition to the issue of which mechanism underlies chartists' faith in TA, a no less important issue is that relating to the method's psychological concomitants. If TA does not result in systematic extra profits for its adherents (Kubińska et al., 2018), what benefits does it bring them? It must provide something since time and resources are invested in learning its techniques and in conducting analyses. If gains are not financial TA might have some psychological utility for its users, just as excessive trading provides a psychological rather than a financial incentive to traders (Markiewicz & Weber, 2013). We suspect that the mere act of classifying an unknown pattern (with no feedback regarding the classification's correctness) increases an investor's confidence. Such a mechanism would resemble possible reduction of a patient's stress (possibly caused by ambiguity aversion) when their symptoms are finally diagnosed as being caused by a certain illness. As "better the devil you know than the devil you don't", having an identified illness is probably not as stressful as having one which is yet to be identified. Similarly, Zaleśkiewicz, Gąsiorowska, Stasiuk, Maksymiuk, and Bar-Tal (2016) argue that doctors and financial advisors are usually considered to be more professional when they recommend action than when they recommended no action/waiting.

An alternative mechanism would be one in which, in the absence of feedback regarding the correctness of TA pattern classifications, a person believe that they are a skillful TA practitioner, which in time may contribute to the development of overconfidence. Thus, based on the above premises and on the general prevalence of overconfidence among financial decision makers (Kubińska et al., 2018; Kubińska & Markiewicz, 2013), it would be expected that the mere act of categorizing charts can result in overconfidence among chartists. Given that overconfidence may be operationalized as a state where subjective accuracy is greater than objective accuracy (Moore & Healy, 2008), we assumed that chartists' overconfidence would be revealed through their perceptions of accuracy in recognizing TA signals being greater than objectively warranted. We therefore tested the following hypothesis:

H2: Chartists overestimate their ability to identify TA figures in trend series presented to them.

Investors' levels of faith in TA may also depend on individual differences, and the present work therefore examined whether one individual factor (need for cognitive closure) might foster the use of TA. As the financial decision-making processes can be often long and elaborate, we considered need for cognitive closure as an individual difference factor because it militates against the use of such complex processes, disposing a DM with a high need for cognitive closure to reach a conclusion as quickly as possible (by omitting evidence relating to categories B, C, and D). Kruglanski (1989) defined need for cognitive closure as "the desire for a definite answer on some topic, any answer as opposed to confusion and ambiguity" (p. 14). Thus, someone with a high need for cognitive closure has a high desire to make clear-cut decisions, reached by obtaining any answer, even when such an answer is not optimal and may be incorrect, just to alleviate the need for further information processing: such individuals are assumed to refrain from processing further information once they have achieved closure. As a result, individuals with a high need for closure are more likely to use information which is available early when forming judgments. Consequently, after reaching closure using initial information, they do not confront their decisions with other subsequent, possibly conflicting, information. Thus, their information processing is superficial and fosters confirmation-oriented reasoning, with information search confirming (and not disconfirming) the data they are considering. The situational perceptions of people with a high need for cognitive closure are simplified but offer a sense of uniqueness, predictability, and order in the world, all of which they desire. Since TA simplifies information processing, making it more superficial (no fundamental information is necessary), preferences for TA may be stronger among investors with a high need for cognitive closure. Thus, our final hypothesis was:

H3: TA usage is positively related to the need for cognitive closure.

Specifically, we expected TA usage to be positively related to scores on the Desire for Predictability subscale of the Need for Closure Scale (Webster & Kruglanski, 1994) as this subscale directly relates to idea that events are repetitive in their nature ("When dining out, I like to go to places where I have been before so that I know what to expect", „I prefer to socialize with familiar friends because I know what to expect from them") and people have – to some extent – the ability to predict the future

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(e.g., “I dislike unpredictable situations”, “I don’t like to go into a situation without knowing what I can expect from it”).

Two studies were conducted to test the hypotheses: an experimental study and a questionnaire study.

METHODOLOGY

2.1. Participants

Forty-nine participants took part in the study. Males formed 65% of the sample. The study was conducted during the Technical Analysis course taken by third-year undergraduate students studying the Capital Markets major in the Faculty of Finance at Cracow University of Economics. Participation was voluntary, but encouraged by a researcher who was not an associate of the TA course teacher. The same independent researcher described the study to participants to obtain their informed consent before experimentation commenced. The work described was carried out in accordance with the Declaration of Helsinki for experiments involving humans. Although no monetary incentives were provided, participants were given bonus credits for the Technical Analysis course. This was intended to provide greater motivation than any minor monetary payoffs that might have been offered instead.

2.2 Procedure

2.2.1. The experimental study. Participants were told that they would see 60 charts presenting a mixture of TA formations and randomly generated price movements (Brownian motion). However, they did not know the proportions of charts falling into each of the two categories. The task materials (see the extract presented in Figure 1 and the complete list of graphics in Appendix – A) were constructed to contaIn

- Group A pictures: 20 clearly visible price formations (one formation per chart, one specific formation per set of charts).
- Group B pictures: 20 blurred price formations (the same as in the previous category, but not as easy to discern).
- Group C pictures: 20 randomly generated price movements (created as described below), judged in a pilot study by competent judges as not containing any specific price formation.

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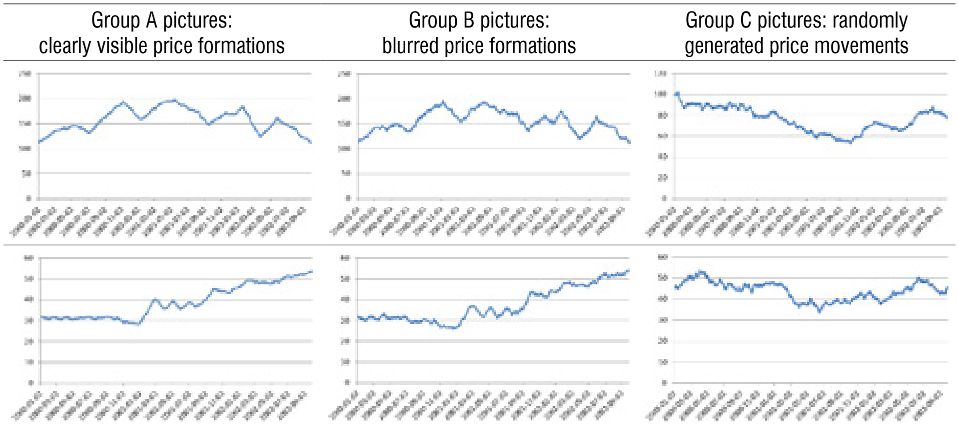

***Figure 1*. Examples of 6 stimuli used in the experimental study (a full list of the 60 stimuli used is presented in Appendix A)**

Graphical broken line representations for each formation, as presented in Murphy (1999), were used as the basis for Group A stimuli.

For Group B stimuli, first we randomly selected an initial value from a uniform distribution on the interval [10,200] and then the time series was rescaled. Then, additional noise was added using a Brownian Bridge stochastic process with initial and terminal values set to 0, terminal time set to 1, and the number of generated numbers set to 1000. The Bridge function of the R sde package (Iacus, 2009)2009 was used for this purpose. Next, the Brownian Bridge time series was variously multiplied by 0.1, 0.2, 0.3, 0.4, 0.5 and 1, and added to basic presentations of formations (Group A stimuli). Thus, we created a total of seven versions of stimuli with different degrees of blurring. Final selection of stimuli was done by visual inspection.

For randomly generated price movements (Group C stimuli), geometric Brownian motion was used. We applied the GBM function of the sde R package (Iacus, 2009)2009. With an initial value of 100, sigma = 1%, and r = sigma^2, $T = N =$ 1000, we generated 1000 values. For the following time series, we randomly selected an initial value from a uniform distribution on the interval [10,200] and sigma from the same distribution (0.5%, 2%). For each time series, Wald-Wolfowitz random runs tests were applied using the runs.test /randtests/ implementation in R (see Mateus and Caeiro (2014).

The whole experimental task was computerized using Lime Survey (Schmitz, 2015) and price formations were presented in random order. Participants first had to decide whether charts presented randomly generated price movements or a TA formation and, if the latter, choose the name of the formation among the 20 alternatives provided. After giving their answer, participants were asked to judge their confidence in their answer using a 0% to 100% scale, where 0 indicated "I chose at random" and 100% represented "I am 100% sure" (Larrick, Burson, & Soll, 2007; Moore, 2007; Moore & Healy, 2008). By comparing each participant's average stated confidence with their true verified ability to distinguish TA signals, the extent to which they overestimated their abilities was identified (Moore, 2007).

2.2.2. The questionnaire study. Students were asked to complete a set of questionnaires during the first class of the course. A test battery was administered online via the Lime Survey platform. The set of tests began with demographic questions and then proceeded as follows:

Propensity for technical analysis. This was measured in two ways:

Q.1) The extent to which participants used (a) technical analysis, (b) fundamental analysis, (c) recommendations, and (d) intuition when making investment decisions: four sub-questions, one for each approach, involving a scale from 1 to 5, where 1 = "Doesn't influence my decisions at all" and 5 = "Significantly influences my decisions".

Q.2) Attitudes toward the following TA methods: (three sub-questions with 1 to 5 scales, where 1 = "Definitely will not bring extraordinary profits" and 5 = "Will bring extraordinary profits":

- Basic analysis of charts: for example, resistance lines, trend lines, moving averages, etc.
- More advanced formations: for example, head and shoulders, crab downward/upward, butterfly downward/upward, bat downward/upward, etc.
- Analysis of indicators: RSI (Relative Strength Index), CCI (Commodity Channel Index), MACD (Moving Average Convergence Divergence), stochastic oscillators, etc.

As the final part of questionnaire battery, the Need for Closure Scale (NFCS) was used (Webster & Kruglanski, 1994) in the form of a revised short (15-item) version adapted for use with Polish samples by Kossowska et al. (2012). This test consists of five subscales: Desire for Predictability, Preference for Order and Structure, Discomfort with Ambiguity, Decisiveness, and Close-mindedness.

Results

3.1. The experimental study

Descriptive statistics for the experimental study showed that recognizing TA patterns is not an easy task (Table 2). For clear formations, an average of 8.61 patterns out of 20 (43%) were correctly identified, this dropping to 28% for blurred formations.

Table 2
Descriptive statistics for the experimental study (N = 49)

		M	*SD*
20 Clear formations	Number of hits	8.61	1.75
	Any formation detected (regardless of correctness)	17.63	1.48
20 Blurred formations	Number of hits	5.55	2.07
	Any formation detected (regardless of correctness)	15.90	2.61
20 Random trends	Number of hits	5.45	3.10

Interestingly, participants revealed a strong tendency to identify random trends as TA formations. Participants correctly identified 27% of the 20 random trends, but claimed to see formations in the remaining 73% of random trends. Importantly, the number of correct identifications of random trends (M = 5.45, SD = 3.10) did not significantly differ from the number of correct identifications of blurred formations (M = 5.55, SD = 2.07: t[48] = -0.192, p = .849).

In general, participants overestimated their ability to correctly identify trend formations, and participants' subjective performance in TA signal recognition was greater than their objective skills (see Table 3), thereby supporting H2.

Table 3
Subjective and objective performance (N = 49)

	Subjective performance / confidence		Objective accuracy		*t*	*p*
	M	*SD*	*M*	*SD*		
20 Clear formations	70.04	15.25	43.06	8.77	11.532	.001
20 Blurred formations	63.32	16.69	27.76	10.36	13.836	.001
20 Random trends	62.85	18.09	27.24	15.48	10.008	.001

Using the lme4 (Bates, Mächler, Bolker, & Walker, 2015) R package (R Core Team, 2016) we fitted a linear fixed effects model for all trials, with declared confidence in decision (0 to 100) as the DV, and two dichotomous IVs: formation type (IV_1; formation A&B vs. random trend C) and answer correctness (IV_2: objective performance: correct vs. incorrect), and their interaction term as predictors (see Table 4).

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Table 4
Linear mixed effects analysis results: DV = self-declared post-decision confidence (0 to 100). The "Type" takes value 1 for formation stimuli regardless of whether it was a "clear A" or "blurred B" formation type and o for Group C stimuli. The "Correctness" takes value 1 for corrects identification of a true TA formation as an TA formation (regardless of whether a participant later gave the correct or incorrect name of a formation) and corrects identification of randomly generated price movements, and 0 otherwise

		DV: confidence	
Predictor	*Estimate*	*CI*	*P*
(Intercept)	55.24	50.66 – 59.83	**< .001**
Correctness (incorrect)	10.08	7.65 – 12.52	**< .001**
Type (true AT formation)	13.47	11.26 – 15.68	**< .001**
Correctness * Type interaction	-27.84	-31.08 – -24.60	**< .001**
	Random Effects		
σ2		315.54	
$\tau_{00\ ind}$		245.14	
ICC_{ind}		0.44	
Observations		3304	
Marginal R^2 / Conditional R^2		0.062 / 0.472	

The results of the analysis revealed that formation type and correctness of classification had a significant joint influence on confidence. The nature of this interaction is depicted in Figure 2 below.

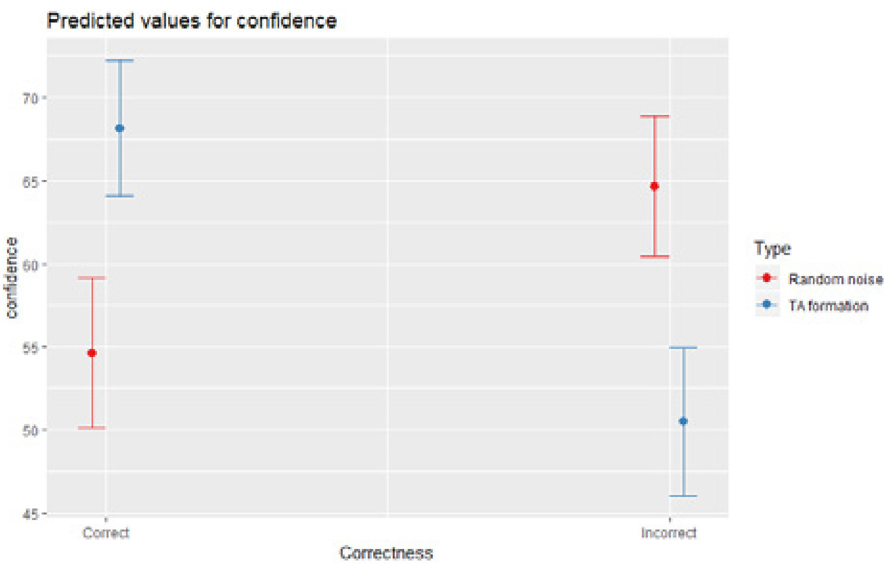

Figure 2. **Self-declared post-decision confidence conditional on IVs (error bars represent 95% CIs). ABDC refers to the evidence classification categories depicted in Table 1**

In line with H1a and H1b, category A evidence instilled more confidence than category C evidence, and, similarly, category B evidence instilled more confidence than category D evidence. Table 4 provides further support for hypotheses H1a and H1b, the table showing that confidence ratings for TA formations were higher for hits than for misses (H1a), and that confidence ratings for random trends were higher for misses than for hits (H1b).

Table 4
Average confidence ratings after choices

	Confidence for hits		Confidence for misses		*T*	*p*
	M	*SD*	*M*	*SD*		
20 Clear formations	76.54	14.09	64.93	17.10	8.149	.001
• Identification of a formation as a random sequence	77.27	13.19	51.91	24.34	8.066	.001
• Identification of a formation as another incorrect formation	76.54	14.09	68.21	16.52	6.693	.001
20 Blurred formations	68.61	15.73	61.09	17.54	5.774	.001
• Identification of a formation as a random sequence	68.68	15.33	51.39	22.08	8.365	.001
• Identification of a formation as another incorrect formation	68.61	15.73	65.03	15.65	2.904	.006
20 Random trends	53.46	24.81	65.86	17.11	-5.657	.001

3.2. The questionnaire study

Hypothesis 3 proposed that the tendency to use TA (and, by implication, a positive attitude toward TA) should be positively related to the need for cognitive closure. This hypothesis was supported, Pearson's *r* analysis showing that global NFCS responses were positively correlated with participants' ratings of TA's influence on their investment decisions (Q.1): $r(46) = .291$, $p < .044$.

The NFCS scale consists of several subscales and it was expected that TA usage would be positively related to desire for predictability scores in particular. Table 5 Panel A shows that this expectation was confirmed, and that, additionally, TA usage was also positively correlated with scores on the discomfort with ambiguity subscale.

Importantly, Panel A of Table 5 also shows that scores on the Need for Closure subscales were not correlated with other approaches to making financial investments (using fundamental analysis, acting on recommendations, and using intuition). Only a preference for using TA related to need for closure (in particular, desire for predictability and discomfort with ambiguity).

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Table 5
Relationships between need for closure and various TA variables

	Panel A				Panel B		
	Q1 – Factors in investing				Q2 – TA approaches		
	Technical analysis	Fundamental analysis	Recommendations	Intuition	Basic analysis of charts	More advanced formations	Analysis of indicators
Preference for order and structure	.201	-.054	.054	.162	.101	.122	.128
Desire for predictability	**.353***	.091	.044	-.060	-.202	.353*	.255
Discomfort with ambiguity	**.366***	-.036	.139	.006	-.185	.320*	.210
Close-mindedness	-.269	.043	.165	-.102	-.175	.021	.007
Decisiveness	.049	.066	-.180	-.256	.082	-.227	-.049

**$p \leq .01$ (2-tailed), *$p \leq .05$ (2-tailed)

Since TA is a broad concept including different methods from basic trend line analysis to indicator analysis, it is useful to know which particular TA approach relates to a need for closure. Results relevant to this issue are presented in Panel B of Table 1, which shows that only the use of more advanced TA formations (e.g., head and shoulders, crab downward/upward, butterfly downward/upward, bat downward/upward, etc.) was related to need for closure.

So, the greater a trader's desire for predictability and discomfort with ambiguity, the greater is the probability that they will take TA into consideration when making investment decisions, and the greater the chances that they will use a TA technique based on analyzing advanced trend formations. It can therefore be concluded that there was strong support for H3 since this hypothesis was verified using two different questions relating to TA.

Discussion

This study examined people's use of dubious data in decision-making processes. Specifically, this phenomenon was examined with respect to people's use of Technical Analysis methods when making investment decisions. Some investors willingly use these methods to support their investment decisions even though evidence for their effectiveness is at best limited.

In the experimental part of the study, TA usage was narrowed down to basic analysis of charts. We demonstrated that subjective accuracy in identifying TA formations is far greater than objective accuracy, this demonstrating overconfidence in TA users (H2). We believe that the mere act of classifying a pattern (in an environment with unclear or no feedback) equips traders with confidence. Just as action is seen as more professional than inaction (Zaleśkiewicz et al., 2016), the act of classifying trends may increase a trader's self-identification as a professional, in turn, this increasing their confidence to the extent that they ultimately become overconfident.

Such a rise in confidence might also be caused by another phenomenon: human difficulties in differentiating between random and non-random (deterministic) sequences (Lopes & Oden, 1987; Williams & Griffiths, 2013). DM's are inclined to identify sequences wherever possible (Tyszka, Markiewicz, Kubińska, Gawryluk, & Zielonka, 2017; Tyszka, Zielonka, Dacey, & Sawicki, 2008). Thus, Zielonka has proposed that TA momentum and contrarian signals are representations of common cognitive biases (Zielonka, 2002, 2004; Zielonka & Białaszek, 2020), and that TA's popularity arises from the pervasiveness of cognitive biases in individual (non-professional) investor's reasoning processes. Chartists believe TA formations to be non-random, deterministic sequences (they believe that the formations they identify are not accidental but emerge because of underlying processes and that they have specific meanings). Other people, even if they identify familiar formations, may believe formations are of random origin and do not form great expectations based upon them. On the other hand, it is known that people form differential expectations toward trends according to whether they are perceived to be random or deterministic (Burns & Corpus, 2004), and it is possible that identifying a trend as a non-random (deterministic) sequence increases confidence purely on the basis of the perceived characteristics of the trend. Thus, it is possible that interpreting a situation as deterministic increases a DM's confidence. This hypothesis should be tested in future research.

We suspected that the general human inability to respond to dubious data (Wojciszke, 2009) may help explain TA's popularity. If this were true, investors should be not be equally interested in all the information that is available (as presented in Table 1): a DM should be more interested in evidence that confirms a hypothesis (A) than in evidence that disconfirms it (C). Such a DM's belief in a hypothesis should be strictly proportional to the strength of information relating to A, as information relating to C can be easily disregarded, superseded, or simply forgotten. Similarly, we thought that evidence relating to B should instill more confidence in such a DM than that relating to D, as the former evidence will be in line with a main hypothesis that is tested initially, before an alternative hypothesis is tested. And, indeed, we found that confidence ratings for TA formations were higher for hits than for misses (H1a) and that confidence ratings for random trends were higher for misses than for hits (H1b). These findings support the idea that confirmation bias contributes to TA's popularity.

In general, the identification of formations raised confidence and recognizing a presented chart as a random sequence decreased confidence (these observations

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were true regardless of whether charts presented TA formations or random prices). It is therefore possible that chartists commence their investigations of price charts with the default assumption that they are viewing a random trend. Then, they look for TA signals. Once a TA signal is recognized (and it does not matter whether this is a true or illusory signal), this signal cannot be "unseen" and confidence increases. On the other hand, if chartists can't notice in the chart anything beyond a random noise, they remain uncertain, as they never know whether, out of nowhere, some type of TA signal will emerge/be identified in a miraculous epiphany/revelation. The suggestion here is that chartists may experience a moment of sudden comprehension that resolves an ambiguous percept and gives them greater confidence. Such moments are often referred to as moments of insight or "Aha! moments (Kounios & Beeman, 2009; Sternberg & Davidson, 1995), and they may increase a chartist's confidence irrespective of whether they relate to a real financial pattern or are illusory.

While the experimental study was restricted to examining TA in terms of the basic analysis of charts, the questionnaire study considered all the tools used by practitioners of TA. We examined relationships between the propensity to use TA tools and the need for cognitive closure, this aspect of the research following a general trend of studies examining the effects of psychological biases and personality traits on investment behavior (Kourtidis, Šević, & Chatzoglou, 2011; Markiewicz & Weber, 2013; Rustichini, DeYoung, Anderson, & Burks, 2016). The results of the questionnaire study supported H3: TA usage was positively related to the need for cognitive closure. In particular, it was correlated with a desire for predictability and discomfort with ambiguity. The relationship between this individual difference variable and a passion for TA can explain the heterogeneity in TA usage among investors. Since, by its very nature, the usage of TA facilitates quick financial decision making, this result suggests that TA may provide useful tools for a certain type of trader: those who have a psychological need to make quick decisions when analyzing advanced formations.

In ending, we should list limitations of the current research. As participating students were non-professional investors, the study should be repeated with professional traders probably more experienced in TA usage. Also, studying more sophisticated individual (non-professional) traders would further validate the present results. Finally, throughout the paper we have argued against TA usage, but we should acknowledge that some studies suggest that TA tools can sometimes have predictive power – reviews of such research can be found in Lo et al. (2000) and Lo and Hasanhodzic (2010, pp. 153-161). For example, empirical evidence suggests that TA may be profitable in foreign exchange markets (Charlebois & Sapp, 2007). This is attributed to the absence of a central order book in such markets and the potential of TA tools to fill this gap.

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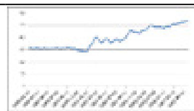
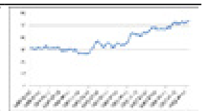
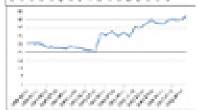
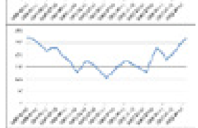
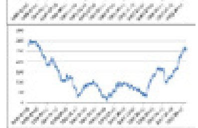
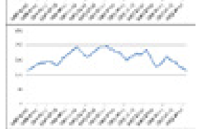
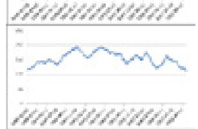
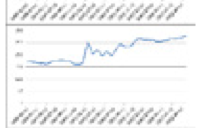
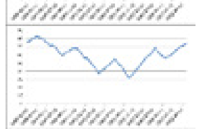
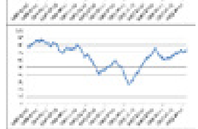
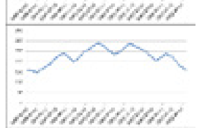
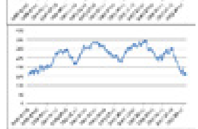
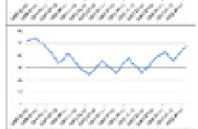
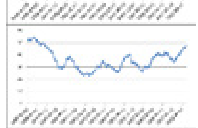
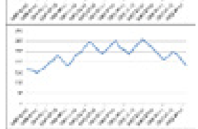
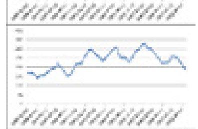
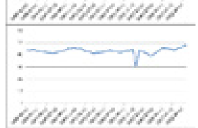
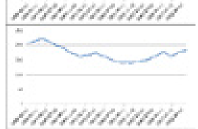
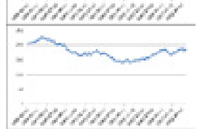
Supplementary materials:

Appendix A

List of the formations used in the study, with Wald-Wolfowitz random runs test results (p values)

	Clearly visible price formations	Blurred price formation	Clearly visible price formations	Blurred price formation
	p values	p values	Screenshot	Screenshot
1. Pennant	0.0000	0.0562		
2. Flag	0.0000	0.0016		
3. Inverse head and shoulders	0.0000	0.8503		
4. Head and shoulders	0.0000	0.0509		
5. Wedge	0.0000	0.0232		
6. Double bottoms	0.0000	0.0777		
7. Double tops	0.0000	0.4864		
8. Triple bottoms	0.0000	0.5676		
9. Triple tops	0.0000	0.0016		
10. Spike	0.0228	0.3198		
11. Cup	0.0000	0.0784		

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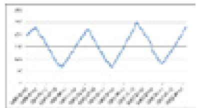
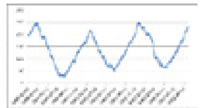
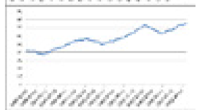
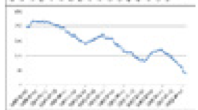
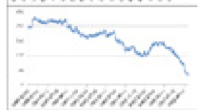
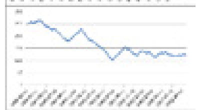
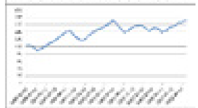
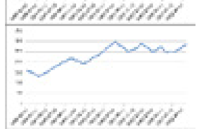
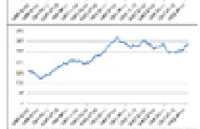
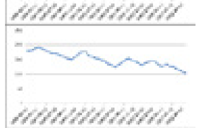
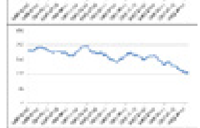
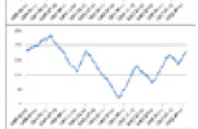
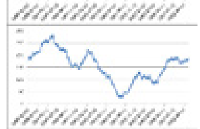
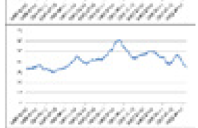
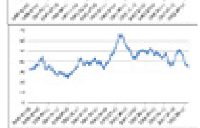
	Clearly visible price formations	Blurred price formation	Clearly visible price formations	Blurred price formation
	p values	*p* values	Screenshot	Screenshot
12. Sideways trend	0.0000	0.0001		
13. Uptrend	0.1672	0.1561		
14. Downtrend	0.6903	0.7482		
15. Descending triangle	0.0075	0.3421		
16. Ascending triangle	0.0000	0.0237		
17. Symmetrical triangle	0.0000	0.2367		
18. Inverse symmetrical triangle	0.0000	0.1885		
19. Falling fan	0.0000	0.8574		
20. Rising fan	0.0000	0.0010		

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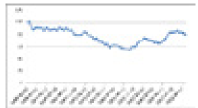
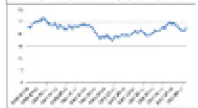
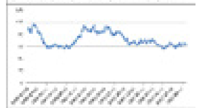
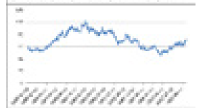
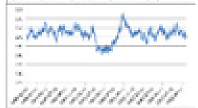
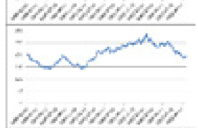
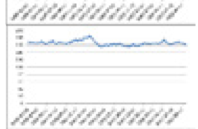
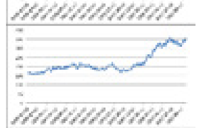
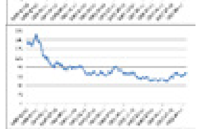
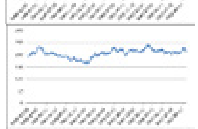
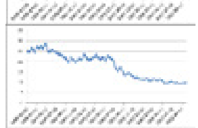
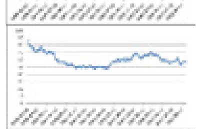
	p value	Screenshot
Random 1	0.5495	
Random 2	0.8002	
Random 3	0.8519	
Random 4	0.7883	
Random 5	0.0660	
Random 6	0.8026	
Random 7	0.9521	
Random 8	0.5040	
Random 9	0.7345	
Random 10	0.0298	
Random 11	0.7923	
Random 12	0.5690	
Random 13	0.3083	

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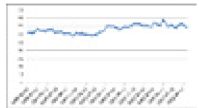
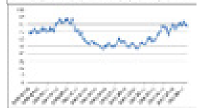
Random 14	0.9494	
Random 15	0.5721	
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Random 17	0.2085	
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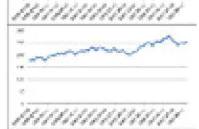
Random 19	0.7526	
Random 20	0.5775