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Abstract

People often live and work in chaotic environments, and thus need to forecast and control what will happen next. The management of chaos is an apparently rare skill, and it would be valuable to identify and develop this skill in the workforce. Untrained undergraduates (*N* = 147) forecasted number series from four chaotic attractors of varying levels of complexity. They contributed measurements of 16PF personality traits, general intelligence, field independence, and divergent thinking. The results indicated that field independence and personality traits associated with the creative personality profile were the most frequent correlates of performance on forecasting one to four steps into the future. It should be possible to adapt the experimental results to personnel selection and placement decisions that require the search for talent for forecasting.

Keywords

Chaos, Forecasting, 16PF traits, Creativity, Divergent, Complex systems

1. Introduction

People live and work in complex systems that exhibit chaotic behavior that they often need to predict and control. Examples include managing supply chains (Sterman, 1988) manufacturing processes (Guastello, 2002), biomedical phenomena (Liebovitch, 1998; Sturmberg & Martin, 2013; West, 2006), economic and ecological systems (Dore & Rosser, 2007; Faggini, 2009; Hommes & Rosser, 2001), robot swarms (Trianni, 2008), work and organizational behavior (Guastello, 2002, Guastello, 2017; Karwowski, 2012; Navarro et al., 2013), and civil unrest and war (Guastello, 1995; Spohn, 2008).

The ability to forecast chaotic events is an important factor in maintaining a balance between a system's stability and its optimum level of variability for adapting to the environment (Schuldberg, 2015). Accordingly, effective control requires the ability to anticipate a trajectory of events over time (Guastello, 2002). Although numerical prediction of chaotic events can be challenging enough (Guastello & Gregson, 2011), real-world demands are often unamenable to freezing the system in order to build a data base and conduct statistical analyses, particularly in emergency situations when volatile events transpire quickly (Baber & McMaster, 2016; Farazmand, 2007; Koehler, 1995). It is important, therefore, to understand individual differences in the intuitive ability to forecast chaotic events, if the goal is to identify and develop talent for careers requiring forecasting ability.

Chaotic series of events can be produced from a multitude of interactions among subsystems or agents. Although it resembles a random process, chaos is deterministic and can be described by relatively simple equations (Sprott, 2003). Several dozen chaotic systems are known, and they produce structurally stable patterns called *attractors*. An attractor is a topological structure that draws objects into its range of influence. A *chaotic* attractor is distinguished from simpler attractor types by its complex internal motion, unpredictability, boundedness, and sensitivity to initial conditions (Lorenz, 1963). The latter is known as *the butterfly effect* (Dooley, 2009).

Attractors can be grouped into categories based on shared characteristics. One distinction of interest is between persistent or anti-persistent time series of data produced by the attractor function. Persistent attractors are those in which observations are more likely to be followed by observations changing in the same direction; if the values of the time series measure are increasing, the next value is also likely to be increasing as well. Conversely, anti-persistent attractors are those in which observations are more likely to be followed by observations in the opposite direction, Differences in forecasting performance on persistent and anti-persistent attractors are pursued further in the experiment that follows.

This study introduced a new question: Can the ability to forecast chaotic events be predicted from cognitive and personality variables? If the supporting individual traits could be identified, they would be widely useful for selecting or training personnel for jobs where forecasting chaos is a prominent component of their cognitive work. The next sections of this article elaborate on what is known about the cognitive operation of forecasting chaos and the cognitive and personality characteristics of people with closely related forecasting skills. To maintain clarity, we use "forecasting" to refer to the cognitive action of the research participants and "prediction" to refer to the statistical operation of modeling the precursors to the participants' accuracy levels.

1.1. Forecasting chaotic numbers

There are two known strategies for researching the ability to forecast chaos: tasking participants to forecast chaotic numbers, and dynamic decision tasks. In the former experimental paradigm, the research participants were presented with a brief series of numbers that were generated from the attractor formulae. Sample time series from the four attractors plus two others that were included in the present study appear in Fig. 1. The visual patterns shown for the samples continue with very long time series, assuming that any underlying control parameter does not change. The logistic map and Hénon attractors would be examples of anti-persistent time series. The Sprott and Lorenz attractors are comparatively more persistent.

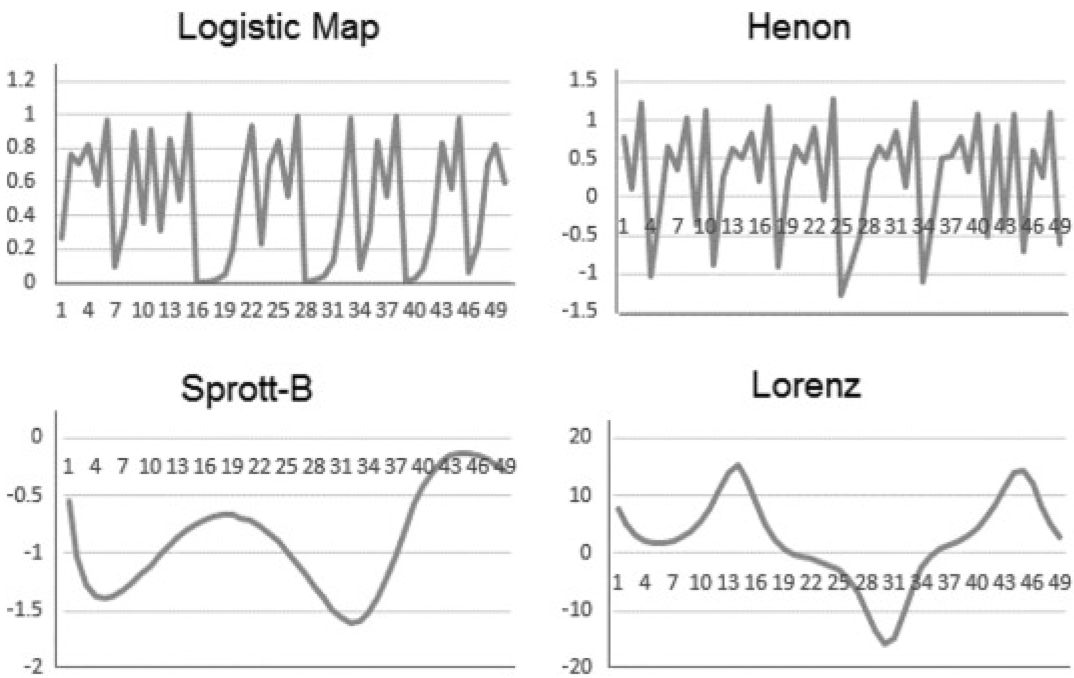

Fig. 1. Sample time series of the logistic map, Hénon, Sprott-B, and Lorenz attractors, 50 iterations each.

The participants were then asked to forecast the next one to four numbers in the series. The correlation between participants' responses and the actual values comprised the measure of accuracy. Individuals' accuracies ranged from 0.45 to 0.99 with the logistic map (Neuringer & Voss, 1993), and from −0.31 to 0.76 with the Hénon attractor (Metzger & Theisz, 1994), both with $N < 10$ adults. Ward and West (1998) reported an accuracy range similar to that of Neuringer and Voss. A fourth study with the Hénon attractor ($N = 40$; Smithson, 1997) produced a mean accuracy of 0.71, which was substantially better than the participants' ability to forecast random numbers (mean $r = 0.18$).

A fifth study (Heath, 2002) examined forecasting accuracy of up to four steps ahead. Unlike the experiments by Neuringer and Voss (1993) or Ward and West (1998), the participants were not given feedback in order to examine ability rather than capacity to learn specific attractors. Accuracy results were best for forecasting one step ahead, roughly tied but lower for two and three steps ahead, and generally poor for forecasting four steps ahead. Mean correlations for accuracy ranged from −0.10 to +0.15 (N = 12), depending on how many steps ahead the participants were forecasting.

After a lull in this research area, a new experiment (Guastello et al., 2019) indicated that participants' performance varied by type of chaotic attractor, with better performance for more complex attractors; whether the attractor was persistent or anti-persistent, with better performance for relatively persistent attractors; and how many steps were forecasted into the future. Forecasting performance being highest for the first forecasting step and lowest for the third; there was an unexpected rebound at the fourth step.

1.2. Dynamic decisions

In the studies requiring participants to forecast chaotic number series, the accuracy of the participants' forecasts did not impact the generation of subsequent stimuli. In a dynamic decision paradigm, the responses made by an agent impact the decision options in the next situation (Brehmer, 2005; Osman, 2010). There were three such experiments with dynamical decisions that required the forecasting of chaotic trends was an object of the analysis. They involved the management of a supply chain, household finances, and commercial fisheries.

The supply chain problem was represented as a computer simulation of a beer distribution enterprise (Sterman, 1988, Sterman, 1989, Sterman, 1994). The dynamics of supply and demand, under conditions of perturbation were known to be chaotic in nature (Sterman, 1988). The participants were graduate students in business administration and professional economists. Their objective was to maintain a supply of beer, place sufficient orders with the breweries and deliver proper quantities to final sales outlets. Participants needed to maintain an equilibrium between the two extremes of running out of beer and overflowing the warehouse. After a series of exposures that were intended to establish an equilibrium in inventory, the program produced perturbations in supply and demand that induced a chaotic regime in inventory levels. Only 12% of the participants were successful in maintaining inventory between the two boundary conditions. Unsuccessful participants were overly focused on the demand dynamics while overlooking the supply dynamics, misinterpreted time lags in the supply, and misinterpreted of the consequences of their choices.

Real-world complex systems involve processes with multiple parameters, which agents mentally update, often incorrectly, in an effort to minimize their errors. Economic agents are not always able to distinguish a stochastic process from a chaotic process, however, and two types of outcomes could result (Hommes & Rosser, 2001; Sorger, 1998). The *perfect forecasting equilibrium* occurs when agents are aware of the actual dynamics, and their decisions produce smooth dynamics and a steady state. The *consistent expectations equilibrium* occurs when agents assume a stochastic process, and their decisions produce chaotic results as they try to compensate and adjust the decisions that they made by using an autoregressive forecasting strategy. Sorger (1998) examined these assumptions and results using an analysis of a mathematical model for household finance in which the households adjusted their spending in the face of income, taxes, expected interest rates, and need for savings. Hommes and Rosser (2001) performed a similar type of analysis of fishing harvests, which have particularly complicated dynamics, involving fluctuating market prices and competition with other agents for open access supplies of fish. They found that the stochastic thinkers took actions that unintentionally produced chaos in the economic environment, leading to a self-fulfilling prophesy that the process is chaotic, even though the dynamic system could have been relatively tame if it were handled correctly.

1.3. Individual differences in forecasting skill

Several efforts to examine forecasting skill arrived at similar conclusions regarding the cognitive and personality traits of the better performing individuals, most of which underscore the central role of divergent thinking and creative personality. One explanation for the connection is that divergent thinking occurs in the non-dominant cerebral hemisphere, which is also where the visual-spatial processing center is located and where new images and situation scenarios are generated (Abraham et al., 2008; Loye, 2000).

One type of divergent thinking is the ability to make remote associations (Guilford, 1968). For instance, the Consequences test (Guilford & Guilford, 1980) asks questions such as, “What would happen if people no longer needed to sleep?” Respondents would give some immediate or obvious implications and some implications that were more remote, e.g., consequences of a consequence. From the perspective of producing creative technological advances, a professional would need to make remote associations in order to evaluate the risk/reward value of various ideas, and possibly multiple forecasts for each idea (Mumford et al., 2009; Sternberg & Lubart, 1995). Forecasts might entail identifying possible negative side effects (e.g. of a medicine), revenge effects (Tenner, 1996), in which a plausible solution to a problem actually makes the problem worse, or the disruptive effect on the status quo and the implication thereof (West & Scafetta, 2010).

In the case of forecasting chaotic or other nonlinear dynamical processes, divergent thinking would generate multiple possibilities for the continuation of the visible trend. The time series in Fig. 2, which was not intentionally a chaotic function. If the segment in Epoch 1 is followed by the segment in Epoch 2, what is the temporal pattern that is likely to occur next? There are several possible correct answers, depending on the mathematical model one assumes.

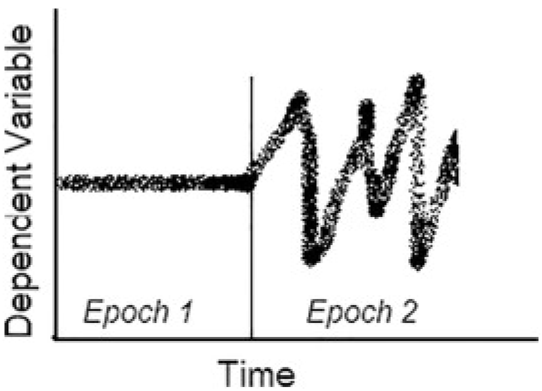

Fig. 2. Hypothetical time series of a nonlinear dynamical process.

Reprinted from Guastello (2011, p. 62), “Frequency distributions and error functions,” in S. J. Guastello & R.A.M. Gregson, *Nonlinear dynamical systems analysis for the behavioral sciences using real data*, with permission of Taylor & Francis.

The empirical studies on individual differences in forecasting ability are limited, but supportive of the general arguments just outlined. Mellers et al. (2015) identified “superforecasters” of political and economic events who also scored higher than other participants in the study on several measures of fluid intelligence, verbal ability (crystalized), and political knowledge at the time when the intake data were collected. The “superforecasters” also expressed a stronger motivation to improve their forecasting skills, seek new information, and update their beliefs and forecasts with new information. This description strongly resembles openness to experience, a personality trait that has been consistently linked to creative behavior (Feist, 1998). Hoffman et al. (2017) drew a similar conclusion about weather forecasters, who commonly work in teams that share and update their information sources and forecasting progress.

Loye (1995) studied creative teams in the movie industry and noted that the movie houses sometimes produce movies on similar themes at approximately the same time. Although it might appear that the movie companies were stealing ideas from one another, Loye attributed the similarity of movie themes to an underlying ability to forecast cultural trends and preferences and organize their movie production schedule accordingly. He found successful forecasting was more likely among individuals who displayed the creativity syndrome of cognitive and personality traits; the latter included open-mindedness, tolerance of ambiguity, and sensitivity to systems thinking.

Poore et al. (2014) also examined forecasting accuracy for political and economic events with regard to aptitude (i.e., GRE, math numeracy), personality, and cognitive style. Their results indicated that aptitudes were the strongest predictors of forecasting accuracy. The other variables primarily affected confidence, which mediated the relationship between aptitude and performance. In terms of simple effects, Poore and colleagues also found a negative relationship between conscientiousness and forecasting skill. Conscientiousness has been regularly shown to be inversely related to the creative personality profile (Cattell & Drevdahl, 1955; Feist, 1998; Guastello, 2009), therefore supporting Loye's (1995) conclusions.

Additionally, there is reason to speculate that individual differences in forecasting skill may be similar to the individual differences in work performance that are connected to workload and fatigue, which can cause performance to fluctuate substantially over time. Cognitive workload is the amount of information of a given type that a person is expected to process in a given way in a fixed amount of time. Several variables were identified as contributing to adaptive responses to workload in a forecasting task that used the chaotic number series paradigm: field independence, anxiety, conscientiousness, and coping flexibility (Guastello et al., 2020). Fatigue is the loss of work capacity as a function of the amount of time spent on a particular task, although it is sometimes confounded with sleep loss. General intelligence and field independence acted as compensatory abilities that supported the main performance goals and buffered the effects of fatigue.

1.4. The present study

The objective of the present study was to identify traits that predict the ability to forecast chaotic numbers. The study was framed as a personnel selection problem: Find the array of cognitive and personality traits associated with the best forecasting performance. To enhance external validity and possible generalizability, the performance task was defined to reflect some real-world constraints:

1. When presented with a new situation requiring forecasting, one does not know in advance which chaotic function is operating. Thus, the stimuli for four types of chaotic structures were presented without any announcement as to what function produced them or when the attractor switched during the experiment.

2. The concern was to describe and predict the participants' level of innate ability to recognize and interpret patterns rather than examining whether learning was possible. Thus, no explicit feedback was given as to whether the participant forecasted correctly.

3. The task and stimuli were presented without reference to a specific context, such as weather finance, disease epidemics, or agriculture

1.5. Cognitive abilities

The distinction between convergent and divergent thinking, the latter being associated with creative thought processes, first arose in conjunction with Guilford's (1968) theory of intelligence, in which 120 cognitive abilities could be defined as a combination of one of several types of input, process, and output. In the next major advance, Cattell and Horn (1978) developed a hierarchical theory of intelligence in which general intelligence is positioned in the top tier of the hierarchy, followed by crystallized and fluid intelligence in the second tier, followed by more specific abilities in the third tier. If one examines the constructs of divergent thinking developed by Guilford and the measures of fluid intelligence in Hakstian and Cattell (1978), the measurement constructs of fluency, flexibility, and originality are virtually the same in both contexts.

In a later development, Sternberg (1999) advanced the triarchic theory of intelligence that consisted of three pillars: convergent or crystallized thought, creative or divergent thought, and practical intelligence. Practical intelligence was the ability to learn from experience and to apply one's knowledge or abilities to practical problems. Learning from experience appears to be another example of fluid intelligence once again, but channeled in a different direction. Carroll (1993) examined empirical studies of cognitive ability measurements and concluded that there were several constructs falling in between general intelligence and the narrowest level of construct measurement, of which crystalized and fluid intelligence were prominent once again. Other expansions of the range of intelligence constructs fall beyond the scope of the present article.

The perspective of neurocognitive studies on working memory, following from Baddeley (2003), indicate that the executive functions of working memory are part of fluid intelligence (Kane et al., 2005). The executive functions of working memory (Ilkowska & Engle, 2010; Miyake et al., 2000) would be required to create or recall mental models of the numeric trend, flip between possible models, and update those models to generate plausible forecasts.

The connection between working memory and fluid intelligence led to the inclusion of field independence as a variable in the present study. Field independence versus field dependence is the ability to identify a target object in a complex visual field and separate it from the background material. It is based on the Gestalt principle of figure-ground distinction. Its primary form of measurement is the Group Embedded Figures Test (GEFT; Witkin et al., 2002), which has a long history of use as a measure of "cognitive style." Field independence has also been studied as a variable in working memory capacity under the reasoning that field independent people can be expected to use more their working memory capacity than field dependent people (Pascual-Leone, 1970). It resurfaced as a relevant variable in the relationship between cognitive workload and performance on tasks that require a person to isolate critical information from extraneous information and hold a number of pieces of information in mind when solving a problem in chemistry (Stamovlasis & Tsaparlis, 2012), financial forecasting (Guastello, 2016) or security system monitoring (Guastello et al., 2016). For those reasons and because of its close connection to other fluid intelligence abilities (Guastello et al., 2019), it was included as a predictor of forecasting success in the present study.

Hypothesis 1 concerns divergent thinking and field independence, and is based on previous work by Loye (1995) and Mellers et al. (2015), and (Guilford, 1968) which indicated that some types of forecasting require an ability to think through the possible behaviors of a complex system and make remote associations. Anagram tests are also well-known measures of divergent thinking (Barron, 1955; Lehman & Gavurin, 1975; Mendelsohn & Griswold, 1964). Performance on an anagram test was correlated with *variability* in performance on a financial decision-making task that required a modicum of forecasting capability (Guastello, 2016). Thus, anagrams were included in this study as a measure of divergent thinking. The role of field independence as an indicator of the efficient use of working memory was described above. To summarize:

Hypothesis 1

Individual differences in divergent thinking and field independence predict the ability to forecast chaotic numbers.

Hypothesis 2

Individual differences in general intelligence predict the ability to forecast chaotic numbers.

1.6. Personality

The portrait of successful forecasters drawn by previous researchers is that they exhibit a full spectrum of traits associated with creative persons more generally. We adopted the hierarchical model of personality as advanced by Cattell et al. (1970; Conn & Rieke, 1994). The two levels of the hierarchy consist of 16 traits that are relatively narrow in scope and definition that are in turn organized into five global traits that are close in meaning to those of the five factor model (FFM; McCrae & Costa, 1985). One of the 16 primary traits (Factor B) is a quick measure of general intelligence, which Cattell regarded as necessary for the proper interpretation of a person's profile on the other 15 traits (Cattell et al., 1970). It was also used to test hypothesis 2. The taxonomy of bipolar traits that make up the current version of the Sixteen Personality Factor Questionnaire (16PF; Cattell et al., 1994) can be divided into two groups for present purposes, those that are more relevant to the creativity profile and those that are not.

Cattell and Drevdahl (1955) characterized the creative person was as (16PF codes in parentheses): aloof or reserved (A−), intelligent or capable of abstract thought (B+), dominant (E+), serious (F−), expedient or inattentive to rules (G−), socially bold (H+), emotionally sensitive (I+), imaginative (M+), open to experience (Q1+) and self-sufficient (Q2+). The other traits are: emotional stability (C), trusting versus suspicious (L), unpretentious and self-disclosing versus politically savvy and private (N), self-doubting versus self-assured (O), impulsive versus self-controlled (Q3) and relaxed versus tense (Q4).

The 16PF global traits resulted from re-analyzing the 16 primary factors, although Cattell et al. (1970) argued against placing too much weight on them precisely because the second-order traits were less specific than the primary 16. Furthermore, because the five factor solution resulted from a previous factor analysis, scales that result from the secondary factor analysis contain another source of error that lies between the final factors and the primary factors, and the primary factors and the original data. Both points strongly suggested that global or FFM traits would be less proximally correlated with external criteria, and there is evidence to support this perspective regard to the prediction of creative behavior (Guastello, 2009). The FFM traits are neuroticism, extroversion, openness, agreeableness and conscientiousness. 16PF second-order counterparts (Cattell et al., 1994) are anxiety, extroversion, independence, tough-mindedness and self-control. Openness is the FFM trait that is most consistently correlated with creative behavior (Feist, 1998), the core concept of which is centered on 16PF Factor Q1.

Hypothesis 3

Personality traits known to be associated with persons who exhibit creative behavior will also be predictive of forecasting ability.

Chaos' characteristics of unpredictability, boundedness, and sensitivity to initial conditions have implications for forecasting. Even though the boundedness of a chaotic attractor means there are global restrictions on the possible states of a system (or values of a variable), the particular state of the system is unpredictable within those global restrictions. Sensitivity to initial conditions means that two objects within a chaotic attractor, which means following the same mathematical rules of motion or change, will not generate the same series of values if they start at slightly different initial values or states. The predictability of a chaotic system at t_1 from t_0 decays rapidly as more time and iterations lapse between t_0 and t_1. It was already shown that participants' performance was best when forecasting one step ahead in time and decayed as they forecasted further steps ahead (Guastello, Futch, Marcisek, Mirabito, Green, and Witty, in press; Heath, 2002). Hypotheses 4 and 5 followed from those results.

Hypothesis 4

The prediction of forecasting performance from cognitive and personality variables will be strongest (as defined by R^2) when predicting performance one step ahead, and psychometric prediction of performance will deteriorate thereafter.

Hypothesis 5

The prediction of performance at steps 2, 3, and 4 can be enhanced by including performance on the previous forecasting step in the regression model.

2. Method

2.1. Participants

The participants were 147 undergraduates, aged 18–24 years, who were enrolled in psychology courses in a Midwestern U. S. University. There were 61 males and 84 females; two participants did not identify their gender. Participants were compensated with course credits.

2.2. Procedure

The experimental sessions accommodated small groups of participants according to the order and time at which they volunteered and were held in a standard classroom that was equipped with desks, chairs, a central computer and a projector screen. After signing the consent form, the participants completed three timed cognitive tests, an untimed survey (not used in the present study), and the 16PF, which was also untimed. The experimental task followed the testing.

2.2.1. Experimental task

The experimental stimuli consisted of 100 PowerPoint slides showing a sequence of eight numbers from one of four chaotic attractors with a graph of those numbers. A sample slide appears in Fig. 3. The task was to predict the next four numbers in the series using a paper and pencil form. The participants were given two practice items, but they were not given any specific context from which the numbers might have originated, nor were they told when the underlying chaotic attractor changed. Each slide was timed for 30 s. The participants were not given any explicit feedback regarding the correct answers.

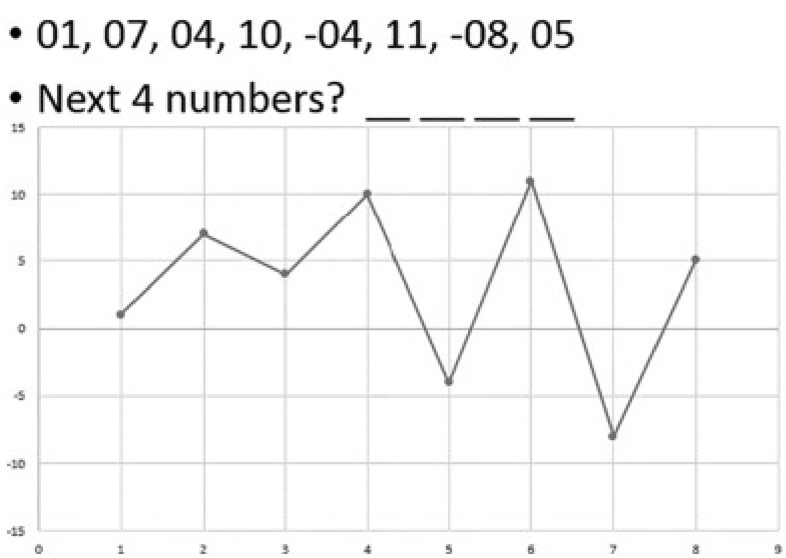

Fig. 3. Sample slide (#86) of eight chaotic numbers.

In one experimental condition, the sequence of stimuli was composed of 20 examples of each of four attractors in ascending order of complexity: the logistic map, Hénon, Sprott-B, and Lorenz attractors. The logistic map and Hénon attractors were chosen for use in this study because they are mathematically simple functions and used by the previous researchers; they were also good examples of non-persistent functions. The Lorenz attractor was included because it produced a relatively persistent time series; it also comes from a class of attractors associated with weather patterns. The Sprott attractor was included because it was also relatively persistent and also from the same mathematical class as the Lorenz attractor, but structurally simpler (Sprott, 2003).

The logistic map series was generated with Eq. (1) a starting value of x = 0.26, and c = 4.0:

$$x_2 = cx_1(1 - x_1);$$

c is a control parameter (May & Oster, 1976; Sprott, 2003).

The other three attractor series were drawn from a library of data file available with the *Chaos Data Analyzer* (Sprott & Rowlands, 1995). The Hénon attractor is perhaps the simplest example of a two-dimensional chaotic attractor:

$$x_2 = 1 - ax_1{}^2 + y_1; y_2 = bx_1.$$

It has two order parameters, x and y, two control parameters, a and b, and a quadratic structure (Sprott, 2003).

The Sprott-B attractor,

$$dy/dx = yz; dy/dt = x - y; dz/dt = 1 - xy,$$

contains three order parameters, x, y, and z. Although there are no additional control parameters, the three order parameters have co-acting effects on each other (Sprott, 2003; Sprott & Rowlands, 1995, p. 44). The Sprott-B attractor is actually a simplification of the Lorenz (1963) attractor:

$$dx/dt = a(y - x); dy/dt = -xz + rx - y; dz/dt = xy - bz,$$

contains three order parameters, x, y, and z. There are three control parameters, a, b, and r. The 80 stimuli were followed by another set of 20 stimuli drawn randomly from the four attractor types.

In a second experimental condition the sequence was reversed: 20 each of Lorenz, Sprott-B, Hénon, and logistic map, again followed by a set of 20 stimuli from randomly chosen attractors. The random sets were included for a separate study on cognitive fatigue (Guastello et al., 2020) and not used here.

The numbers from the series were multiplied by 100 and trimmed to a maximum of three digits to eliminate decimal points. Negative signs were retained. The descriptive properties of the stimuli data are given in Table 1.

Table 1. Descriptive statistics for properties of the attractor time series used to prepare stimuli.

Recoded series	**Logistic map**	**Hénon**	**Sprott**	**Lorenz**
Mean	47.595	2.857	−60.643	12.238
SD	35.959	7.129	102.454	75.789
Minimum	0	−13.00	−289.00	−159.000
Maximum	100.00	13.00	134	163.000
N	84	84	84	84

Table 2 contains the autocorrelation spectra for the four attractors at lags 1–5 (N = 400 observations). Partial autocorrelations are adjusted for all autocorrelations at the shorter lag length. Autocorrelations and partial autocorrelations for the logistic map did not exceed the 95% confidence interval around 0.00. This outcome a random number series, even though it was a deterministic function. The Hénon attractor had five negative partial autocorrelations of small to medium size. The Sprott attractor has five positive autocorrelations that were relatively large; two partial autocorrelations were negative. Similarly, the Lorenz attractor had five large positive autocorrelations; the second partial autocorrelation was negative.

Table 2. Autocorrelations and Partial Autocorrelations for Four Attractors at Lags 1–5.

Lag	Logistic Map	Henon	Sprott	Lorenz
Autocorrelation				
1	0.04	−0.30*	0.98*	0.96*
2	0.08	0.24*	0.92*	0.86*
3	−0.03	−0.38*	0.84*	0.72*
4	−0.06	0.04	0.73*	0.58*
5	−0.07	0.18*	0.62*	0.56*
Partial autocorrelation				
1	0.04	−0.30*	0.98*	0.96*
2	0.08	0.16*	−0.93*	−0.83*
3	−0.03	−0.31*	0.65*	0.36*
4	−0.06	−0.19*	0.10	0.16*
5	−0.06	−0.14*	−0.16*	−0.09

$*p < .05$.

2.3. Measurements

The Group Embedded Figures Test (GEFT; Witkin et al., 2002) presents a simple geometric form and a complex geometric form. The participants were instructed to locate and trace the simple form that was embedded in the complex form. The GEFT consists of a 2-min timed section of practice items that are not scored and two 5-min timed groups of 12 items that are scored. The split-half reliability values of the GEFT are 0.82 based on 177 adults and 0.85 based on 150 college students (Witkin et al., 2002).

The mixed anagram test was developed for use in our lab in studies of cognitive workload and fatigue (Guastello, 2016). There were 15 items; each consisted of a five-letter word that was scrambled with five random digits mixed in. The participant was instructed to isolate the letters and rearrange them into a word. The vocabulary words for the anagrams were picked from words appearing on a test of commonly misspelled words used in previous experiments of cognitive fatigue. The anagram test was delivered in paper-and-pencil format. After giving the instructions and presenting a sample item, the participants were given 7.5 min to complete the 15 items. The alpha reliability for this test was 0.79 based on a laboratory sample of 299 undergraduates (Guastello, 2016).

The third cognitive measure was What If (Guastello, 1994), which is a measure of remote associations. What If consisted of five implausible scenarios to which the respondents gave suggestions about what would happen if the initial premise were true. An example item: “What would happen if pigs suddenly developed the ability to talk?” Although the initial cues tended to evoke humorous responses, the objective of the measurement was to assess how well the respondent could think through a complex situation with social implications. The score on What If was the number of suggestions given that were not redundant or illogically connected to the premise. The scoring for What If was simpler than Consequences, and it only counted one type of forecasted outcome rather than separate scores for obvious and remote consequences. The inter-rater reliability of What If was 0.97 (N = 412; Guastello et al., 2004). What If was also found to be significantly correlated with scores on other divergent thinking measures of ideational fluency (semipartial $r = 0.37$), originality ($r_{sp} = 0.25$), semantic fluency ($r_{sp} = 0.25$), and a personality-based measure of emotional intelligence ($r_{sp} = 0.09$); multiple $R = 0.63$.

The 16PF measurements have high construct validities and strong test-retest reliabilities (Conn & Rieke, 1994). Two general population samples (N = 820 and 2500) and one sample of college undergraduates (N = 1340), yielded internal consistency reliability coefficients for the 16PF primary factors ranging from 0.68 to 0.87 (p. 81), and from 0.70 to 0.86 when all three samples were combined. In a sample of undergraduate students (N = 159), two-month test-retest reliability coefficients ranged from 0.64 to 0.79. The correspondence between the 16PF global factors and the FFM was determined by a factor analysis of global traits and FFM facets. The global factor of introversion vs. extroversion corresponds with the FFM trait extroversion (factor loading =0.67). The global factor of anxiety corresponds to the FFM trait neuroticism (factor loading =0.85). The global factor of self-control corresponds to the FFM trait of conscientiousness (factor loading =0.72). The other two global factors of the 16PF are inversely related to the FFM traits. The global factor of tough-mindedness is inversely related to the FFM trait openness; higher scores in tough-mindedness correlate to lower scores in openness (factor loading = −0.70). The global factor of independence is inversely related to the FFM trait agreeableness; higher scores on independence correlate to lower scores on agreeableness (factor loading = −0.72; p. 134).

Forecasting performance was measured as a correlation between the forecasts given by the participants and the actual values from the mathematical time series. Performance measures were calculated for each attractor (20 items × 4 forecasts = 80 items) and for each step-ahead forecast. The percentage of missing data was counted for each participant, and the accuracy correlations were reduced by the percentage of missing data to produce the accuracy metrics that were used in the statistical analysis.

2.4. Statistical analyses

The first analysis was correlational, investigating the relationships between the forecast accuracies and cognitive and personality variables. 16PF factor B, general intelligence, was included with the cognitive variables.

The second analysis used stepwise multiple regression. The independent variables were the cognitive variables, personality variables, and forecast accuracies from previous steps (not possible for the first forecast). The dependent measures were forecasting accuracy on each of the four forecast steps, by each attractor.

The third analysis investigated the characteristics of the superforecasters. The superforecasters were defined by counting how many times out of 16 the participant produced accuracy correlations greater than or equal to 0.95 after adjusting for missing data. This score was then correlated with personality and cognitive variables to produce a final profile.

3. Results

3.1. Descriptive statistics

The descriptive statistics for forecasting accuracy appear in Table 3 for all forecasting steps and all four steps together for each attractor. The negative performance values indicate that the participant was intuiting the pattern of the attractor somewhat, but was getting the forecasting strategy backwards in places, more so in the case of the anti-persistent attractors.

Table 3. Descriptive statistics for forecasting accuracy measured as correlations with actual numeric values, all levels.

Attractor	**Level**	**Mean**	**SD**	**95CI-Lower**	**95CI-Upper**
Logistic	1	0.07	0.28	0.02	0.12
	2	0.04	0.26	−0.00	0.08
	3	−0.09	0.31	−0.14	−0.04
	4	0.08	0.27	0.04	0.12
	All	0.00	0.13	−0.02	0.02
Hénon	1	0.04	0.28	−0.01	0.09
	2	0.12	0.26	0.08	0.16
	3	0.38	0.22	0.34	0.42
	4	0.14	0.25	0.10	0.18

	All	0.13	0.17	0.10	0.16
Sprott	1	0.79	0.30	0.74	0.84
	2	0.76	0.32	0.71	0.81
	3	0.33	0.21	0.30	0.36
	4	0.63	0.31	0.58	0.68
	All	0.56	0.25	0.52	0.60
Lorenz	1	0.80	0.31	0.75	0.85
	2	0.74	0.31	0.69	0.79
	3	0.63	0.28	0.58	0.68
	4	0.51	0.24	0.47	0.55
	All	0.65	0.27	0.61	0.69

3.2. Bivariate analyses for forecasting accuracy

The bivariate correlations among the accuracy levels for the four attractors are shown in Table 4 for all forecasting steps combined. All correlations were statistically significant.

Table 4. Correlations among predictor performances, four attractors, all forecast levels combined.

Attractor	**Hénon**	**Sprott**	**Lorenz**
Logistic Map	0.19*	0.19*	0.24**
Hénon		0.26**	0.31**
Sprott			0.67***

∗*p* < .05.
∗∗*p* < .01.
∗∗∗*p* < .001.

The bivariate correlations between the accuracy levels for the four attractors and the personality and cognitive variables appear in Table 5. The statistically significant results were sparse. There were no correlations with performance on the logistic map. Scores on What If (r = 0.17, p = .043) and 16PF-I (sensitivity versus tough poise, r = 0.17, p = .038) were correlated with performance on the Hénon attractor. Field Independence was correlated with performance on the Sprott attractor (r = 0.19, p = .018), and 16PF-Q2 (self-sufficiency vs group dependency) was correlated with performance on the Lorenz attractor (r = 0.23, p = .005).

Table 5. Bivariate correlations, cognitive and personality variables with attractors, all prediction levels combined.

Cognitive	**Logistic map**	**Hénon**	**Sprott**	**Lorenz**
GEFT	0.04	0.16	0.19*	0.14
Anagrams	0.00	0.01	0.12	0.15
What If	−0.04	0.17*	0.00	0.00
16PF-B	0.00	0.10	0.08	0.00
Primary personality[a]				
A: Warmth	0.05	0.01	−0.13	−0.09
C: Emotional stability	0.04	0.07	0.04	0.01
E: Dominance	0.08	0.12	0.00	−0.06
F: Friendliness	0.14	−0.01	0.07	−0.02
G: Conscientiousness	0.08	0.12	0.06	0.10
H: Social boldness	0.05	0.12	−0.03	−0.10
I: Sensitivity	0.03	0.17*	0.01	0.02

L: Vigilant	0.06	−0.04	0.03	0.10
M: Imaginative	0.02	−0.11	0.05	0.07
N: Privateness	−0.02	−0.13	−0.05	0.01
O: Self-doubting	0.05	−0.10	0.01	−0.03
Q1: Open to change	0.11	−0.10	0.04	0.16
Q2: Self-sufficient	0.01	−0.04	0.11	0.23**
Q3: Self-controlled	−0.03	0.13	0.08	0.08
Q4: Tense	−0.02	0.10	−0.06	−0.14
Global personality[a]				
Extraversion	0.10	0.10	−0.02	−0.12
Independence	0.10	0.07	0.01	0.01
Tough-mindedness	−0.09	−0.01	−0.04	−0.07
Self-control	0.00	0.14	0.05	0.09
Anxiety	0.00	−0.06	−0.04	−0.06

[a]Personality variables are named after the high-score pole.
$*p < .05$.
$**p < .01$.

Correlations among the cognitive variables appear in Table 6. 16PF-B (general intelligence) was positively correlated with field independence ($r = 0.31$, $p = .001$), anagrams ($r = 0.28$, $p = .001$), and What If ($r = 0.18$, $p = .030$). Field independence was positively correlated with anagrams ($r = 0.23$, $p = .006$). What If was not correlated with field independent ($r = 0.04$, $p = .644$) or anagrams ($r = 0.11$, $p = .195$).

Table 6. Correlations among cognitive variables.

	Anagrams	**What If**	**16PF-B**
GEFT	0.23**	0.04	0.31**
Anagrams		0.11	0.28**
What If			0.18*

$*p < .05$.
$**p < .01$.

Stepwise multiple regression was performed to determine if the cognitive and personality variables that were correlated with performance made independent contributions to the prediction of forecasting accuracy or perhaps would uncover complimentarity effects. Once again, all four forecasts were combined into the dependent measure for each attractor, and there were no correlations with performance on the logistic map. Results for the Sprott and Lorenz attractors did not produce any new results beyond the bivariate correlations previously mentioned. Results for the Hénon attractor were more interesting, however. There were two significant correlates, sensitivity ($\beta = 0.22$, $t = 2.65$, $p = .009$) and dominance ($\beta = 0.18$, $t = 2.17$, $p = .032$), producing a multiple $R = 0.25$ ($F(2,144) = 4.59$, $p = .012$). What If entered the model with the stepwise procedure, but dropped out of the analysis due to variance overlap with the variables that remained in the model.

3.2.1. Multiple Regression for Separate Forecasting Steps

The next analyses considered the possibility that the first of four predictions made by participants could be more accurate than subsequent predictions due to the information decay in a chaotic attractor series over time. Thus, if the forecasts made by participants were virtually all noise or error, there would be little correlation between the research variables and individual differences in forecasting accuracy. If individual differences in forecasting accuracy were meaningful, however, then prediction of performance with cognitive and personality variables would at least be possible. The results from this set of analyses appear in Table 7.

Table 7. Prediction of accuracy on separate attractor forecasts using cognitive abilities and personality traits as predictor variables.

Attractor		**Forecast Level**			
		1	**2**	**3**	**4**
Logistic Map	*R* or *r*	0.28**	0.27***	0.00	0.00
	Variables	GEFT I+	16PF-B		
Hénon	*R* or *r*	0.20*	0.36***	0.27*	0.00
	Variables	GEFT	I+ A− L− Q4+	H+ What If	
Sprott	*R* or *r*	0.18*	0.22**	0.17*	0.18*
	Variables	GEFT	GEFT	GEFT	GEFT
Lorenz	*R* or *r*	0.23**	0.24**	0.23**	0.33***
	Variables	Q2+	Q2+	Q2+	Q2+ G+ Q1+

∗*p* < .05.
∗∗*p* < .01.
∗∗∗*p* < .001.

For the logistic map, the ability to predict the participants' accuracies was fairly strong for the first two prediction levels, but dropped to zero for levels 3 and 4. The two variables that explained accuracy on the first prediction were field independence (β = 0.20, *t* = 2.45, *p* = .016), and sensitivity (β = 0.19, *t* = 2.40, *p* = .019), producing a multiple *R* of 0.28 (*F*(2, 144) = 5.89, *p* = .003). The relevant variables changed for the second prediction, however, to a single variable, general intelligence (*r* = 0.27, *p* = .001). The ability to predict the participants' accuracies dropped to zero for levels 3 and 4.

For the Hénon attractor, participants' accuracy on their first prediction was predicted by field independence (*r* = 0.20, *p* = .018). Participants' accuracy on their second prediction was predicted by four personality traits (*R* = 0.36, *F*(4, 142) = 5.28, *p* = .001): sensitivity (I+, β = 0.26, *t* = 3.10, *p* = .002), reserved or aloof (A-, β = −0.18, *t* = 2.09, *p* = .039), trusting and accepting (L-, β = .-0.21, *t* = −2.55, *p* = .012), and tension (Q4+, β = 0.16, *t* = 2.02, *p* = .045). The prediction model for the participants' accuracy on their third prediction was different, however (*R* = 0.27, *F*(2, 144) = 5.49, *p* = .005); the two independent variables were social boldness (H+, β = 0.18, *t* = 2.24, *p* = .026) and What If (β = 0.17, *t* = 2.24, *p* = .036). The ability to predict the participants' accuracies dropped to zero for level 4.

For the Sprott attractor, field independence was the single predictor of performance on all four predictions made by the participants. Correlations were 0.18 (*p* = .031), 0.22 (*p* = .007), 0.17 (*p* = .036), and 0.18 (*p* = .032), respectively.

For the Lorenz attractor, self-sufficiency (Q2+) was the single predictor of performance on the first three predictions made by the participants. Correlations were 0.23 (*p* = .004), 0.24 (*p* = .004), and 0.23 (*p* = .005) respectively. The explanation for predictions at level 4 was stronger (*R* = 0.33, *F*(3, 143) = 5.70, *p* = .001); the independent variables were self-sufficiency (Q2+, $\beta = 0.22$, $t = 2.75$, $p = .007$), conscientiousness (G+, $\beta = 0.20$, $p = .012$), and self-sufficiency (Q1+, $\beta = 0.19$, $t = 2.54$, $p = .012$).

Field independence was a significant predictor of performance in six models, self-sufficiency was a predictor of performance in four models, sensitivity was a predictor in two models, and eight other ability or personality variables were predictors in one model each. The overall picture was consistent with the creative thinking and personality hypothesis 3. There were two deviations from the profile, however, which were L- and G+ in one model each. Fig. 4 summarizes the *R* coefficients.

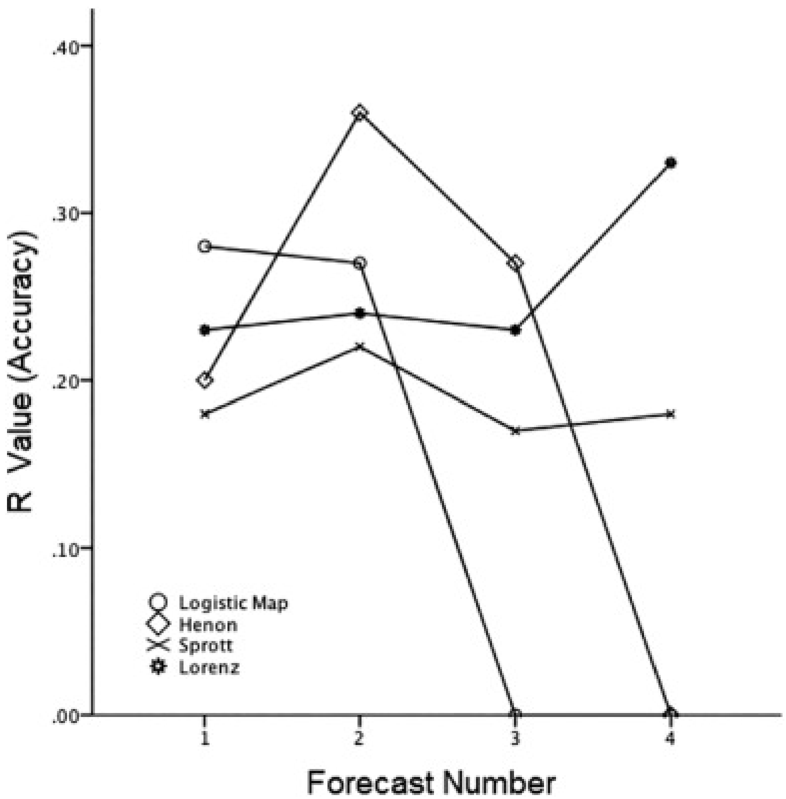

Fig. 4. Plot of multiple *R* for forecasting accuracy predicted from cognitive abilities and personality traits at each forecast step.

3.3. Separate forecasting steps with previous forecasting accuracy

Table 8 summarizes the prediction of accuracy on separate attractor forecasts using cognitive abilities and personality traits again, but with experimental condition and prior forecasts for the same attractor added as independent variables. The experimental condition of ascending and descending algorithmic complexity was included as a dummy-coded variable as an experimental control; if the effect was nontrivial, it would suggest that some implicit learning was occurring as participants gained exposure to simpler or more complex attractors. The prior forecasts for an attractor were included because there was reason to assess the possibility that a particular forecast could be contingent on forecasted values made one step earlier as it would be in a real nonlinear dynamical process.

Table 8. Prediction of accuracy on separate attractor forecasts using cognitive abilities, personality traits, experimental condition, and prior predictions for the same attractor.

Independent variable	**β**	**t**	R^2
Logistic map 1: $R = 0.28$, $F(2,144) = 5.89$**			
GEFT	0.20	2.45*	0.04

16PF-I	0.19	2.37*	0.08
Logistic map 2: *R* = 0.65, *F*(3,243) = 38.59***			
Logistic map 1	0.59	9.22***	0.37
16PF-B	0.20	3.10**	0.41
Condition	0.15	2.36*	0.43
Logistic 2	0.44	5.44***	0.36
Logistic 1	0.26	3.16**	0.40
Logistic map 4: *R* = 0.66, *F*(4, 142) = 27.25***			
Logistic 3	0.39	4.80***	0.35
Logistic 1	0.17	2.05*	0.39
16PF-A	0.16	2.51*	0.40
Logistic 2	0.19	2.21*	0.42
Hénon 1: *R* = 0.30, *F*(2, 144) = 7.28***			
Condition −0.23		−2.92***	0.07
GEFT	0.17	2.06*	0.09
Hénon 2: *R* = 0.39, *F*(5, 141) = 5.18***			
16PF-I	0.24	2.73**	0.05
16PF-A	−0.17	−2.02*	0.08
16PF-L	−0.18	−2.29*	0.10
Hénon 1	0.21	2.55*	0.13
Condition	0.17	2.05*	0.16
Hénon 3: *R* = 0.04, *F*(2, 144) = 5.49**			
16PF-H	0.18	2.24*	0.04
What If	0.17	2.11*	0.07
Hénon 4: *R* = 0.00			
Sprott 1: *r* = 0.18			
GEFT	0.18	2.18*	0.03
Sprott 2: *R* = 0.85, *F*(3, 143) = 125.36***			
Sprott 1	0.85	19.23***	0.71
16PF-A	−0.13	−2.76**	0.71
16PF-O	0.11	2.32*	0.73
Sprott 3: *r* = 0.64			
Sprott 2	0.64	10.00***	0.41
Sprott 4: *R* = 0.86, *F*(5, 141) = 79.92***			
Sprott 2	0.63	11.18***	0.66
Sprott 3	0.30	5.29***	0.72
What If	−0.10	−2.18*	0.72
16PF-I	−0.09	−2.10*	0.73
16PF-F	0.09	2.07*	0.74
Lorenz 1: *R* = 0.39, *F*(3, 143) = 8.64***			
Condition	0.29	3.71***	0.09
GEFT	0.17	2.21*	0.13
16PF-Q2	0.17	2.20*	0.15
Lorenz 2: *r* = 0.96			
Lorenz 1	0.96	41.34***	0.92
Lorenz 3: *R* = 0.95 *F*(2, 144) = 599.96***			
Lorenz 2	0.95	34.59***	0.89

16PF-M	−0.06	−2.20*	0.89
Lorenz 4: R = 0.94 $F(3, 143)$ = 372.79***			
Lorenz 3	0.92	32.30***	0.88
16PF-G	0.09	2.94**	0.88
16PF-Q1	0.06	2.23*	0.89

$*p < .05$.
$**p < .01$.
$***p < .001$.

The overall accuracy of the descriptive regression models improved in many cases. Cognitive or ability variables that were predictive of an earlier prediction accuracy sometimes dropped out of the model on the subsequent analysis and were replaced by the earlier prediction accuracy level itself. This substitution occurred in six models out of nine opportunities for doing so. Prior forecasting accuracy simply accounted for additional variance in logistic map step 2. Prior forecasts had no effect on Hénon steps three or four.

The ascending vs descending condition made a significant contribution to four models out of 16 opportunities for doing so. The effect favored descending complexity as a positive predictor of performance on both the logistic map and Lorenz. Performance on the logistic map benefitted by being present as the first attractor series. Performance on the Lorenz attractor benefitted from being the last of the four attractors presented. The other two condition effects were negative for Hénon forecast 1 and positive for Hénon forecast 2. Performance on the Hénon attractor benefited more from some prior exposure to the Lorenz and Sprott attractors than from prior exposure to the logistic map. The condition effects suggest that some implicit learning about chaotic behavior was occurring. Fig. 5 summarizes the R coefficients for this set of regression models.

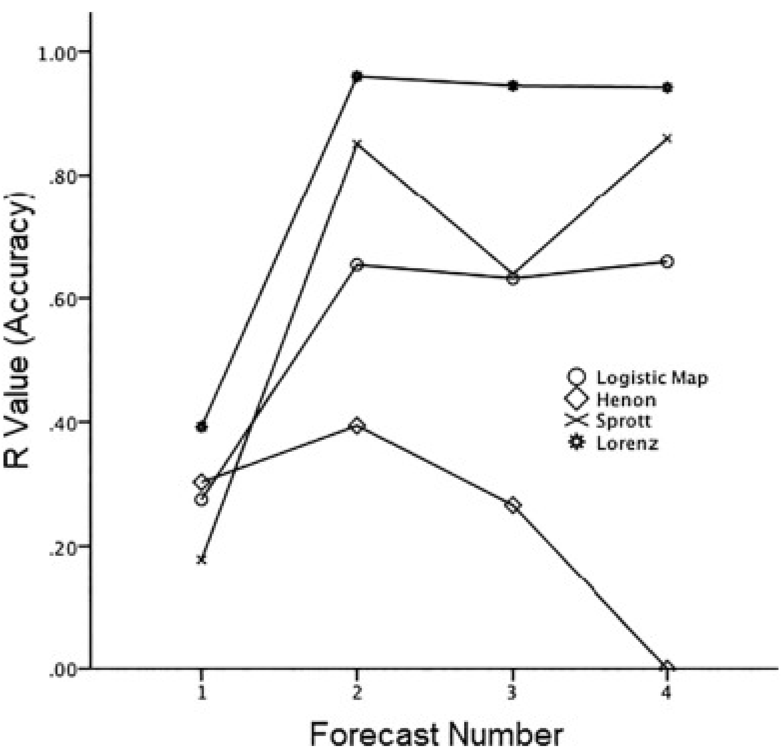

Fig. 5. Plot of multiple R for forecasting accuracy predicted from cognitive abilities, personality traits, prior prediction accuracy, and ascending-descending conditions at each prediction step.

3.4. Superforecaster ability

Superforecaster ability was defined as the number of times a participant reached an accuracy level of >0.95 out of 16 opportunities (four predictions X four attractors). The actual range was 0 to 6 (M = 1.63, SD = 1.37). The distribution (Fig. 6) was bimodal, with 44 cases scoring 0, and 73 cases scoring 2 or 3. Only 8 cases scored >3. Regression analysis showed that superforecaster ability was correlated with only one variable, which was field independence (GEFT; r = 0.18, p = .026).

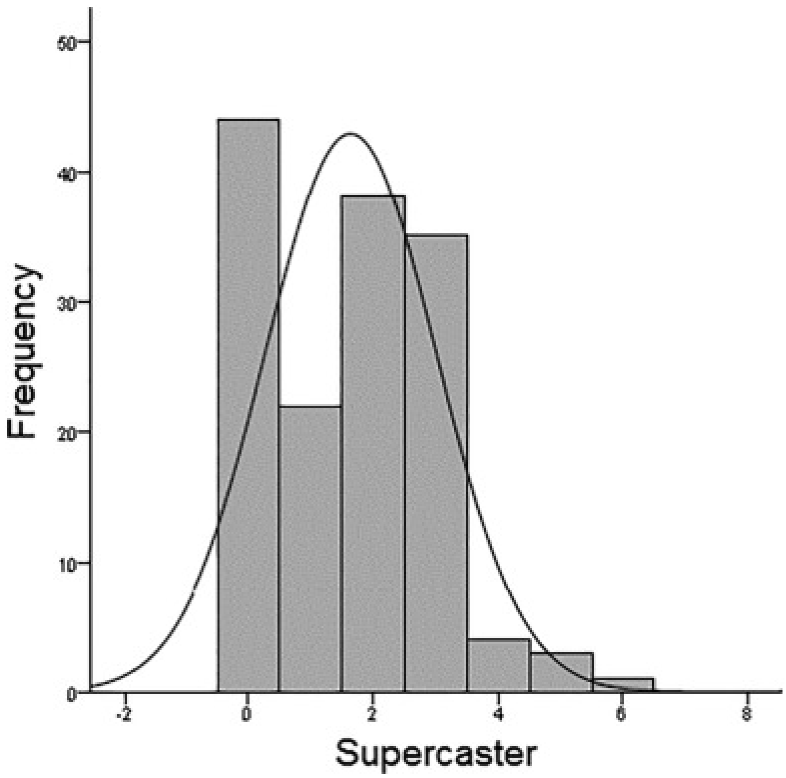

Fig. 6. Distribution of superforecasting ability with normal curve superimposed.

4. Discussion

Many types of work involve forecasting events that are chaotic in nature. The relatively unpredictable quality of chaos led to questions of whether people could naturally predict chaos (in the form of chaotic numbers) or whether they could learn to do so. The early experiments suggested that both were possible. The heuristic of assuming persistence versus anti-persistence (Guastello, Futch, Marcisek, Mirabito, Green, and Witty, in press; Smithson, 1997) goes part way toward deciding or intuiting which type of chaotic process is occurring. Sometimes the deterministic function is known, but often it evolves extemporaneously.

Another type of study utilized an interactive medium in which the actions the participants took on the basis of their forecasts had an impact on the (virtual) system, which could then induce chaos if it was not already there. One dominant heuristic was to search for an equilibrium and then expecting any deviation to return to the equilibrium (Sterman, 1994). As noted previously, agents who understand a chaotic process and manage it accordingly can keep it stable, but those who mistook it for a stochastic process and acted under that supposition would actually induce chaos (Hommes & Rosser, 2001).

The extant research indicated that the prediction of chaos was a relatively rare ability. The unique contribution of the present study was to identify the profiles of personality and cognitive variables associated with this special ability.

4.1. Evaluation of hypotheses

4.1.1. Cognitive variables

Cognitive variables contributed to the stepwise models predicting performance using cognitive and personality variables in eight out of 16 cases (Table 7), thus giving reasonable support for hypothesis 1. When previous forecasting performance and ascending versus descending methods of stimulus presentation were introduced as predictors, cognitive variables still appeared in six out of 16 models. The most frequently appearing cognitive variable was field independence, followed by What If (a type of divergent thinking). At the superforecaster level of ability, field independence was the only unique predictor of performance.

In contrast, general intelligence appeared to play only a small role. It was a unique predictor of performance only once on the second forecast of the logistic map. General intelligence was substantially correlated with the other cognitive variables that were more closely related to forecasting, however. Thus, there was qualified support for hypothesis 2.

Anagrams, however, were consistently unrelated to forecasting performance. It would be fair to conclude, therefore, that the type of divergent thinking represented by an anagrams test was not helpful in the forecasting task used here.

4.2. Personality

The two most frequently appearing personality variables in the regression models for predicting forecasting performance were sensitivity (I+) and self-sufficiency (Q2+), both of which are part of the creative personality profile. Other traits from the profile that made an occasional contribution were aloof instead of warm and engaging (A-), social boldness (H+), and openness to experience (Q1+), thus supporting hypothesis 3.

Two other traits that were not part of the creative personality profile but made one-time contributions were trusting (L-) and conscientiousness (G+). L- seems counterintuitive; if decision makers are expecting chaotic trends one would think they would be on guard for unexpected changes in system behavior. The G+ trait is the opposite of what appears in the creative personality profile; creative personalities tend to look for ways around situational constraints rather than conform to them, and they might forego attention to some details in order to get a job finished. In contrast, G+ in this context could indicate that our better decision makers were trying to track the trends and make their forecasts very carefully.

4.3. Multiple future forecasts

Hypothesis 4, that the accuracy of the regression models would be strongest for the first forecasting step compared to later steps was generally supported for all four attractors. Hypothesis 5, which was that forecasting accuracy on the second, third, and fourth forecasts would be correlated with previous forecasts, was examined along with the predictive value of the cognitive and personality variables on a competitive basis. The accuracy of a previous forecast contributed to the stepwise regression model (Table 8) in ten out of twelve occasions. The combination of personality, cognitive, and previous performance data resulted in higher levels of prediction of performance over time, except in the case of the Hénon attractor where no prediction was possible for the fourth forecast.

4.4. Ability, luck, and superforecasting

The participants showed a substantial range of accuracy, and one might consider how much of the accuracy, which was measured by a correlation between forecasted and actual numbers, could have occurred by chance. There were 80 forecasts per attractor including all four forecasted time periods. The critical value of r at p = .05 is 0.233, and the critical value at p = .01 is 0.302. Only 3.4% of the participants met the 0.05 benchmark on the logistic map, 19.7% met it on the Hénon attractor, and 89.1% met it on the Sprott and Lorenz attractors. Only

2.7% met the 0.01 benchmark on the logistic map, 10.9% met it on the Hénon attractor, 86.4% met it on the Sprott attractor, and 88.4% met it on the Lorenz attractor. It was clear from these numbers that successful forecasting was not due to chance, and some attractors were more difficult to forecast than others. Importantly, there were some relatively consistent predictors of performance throughout the analyses; if forecasting accuracy was only a matter of chance, it would not be correlated with other variables.

Superforecasters were defined as those whose accuracy scores on specific attractor-level combinations met or exceeded 0.95. For a correlation based on 20 stimuli, the critical values of r at $p = .05$ and $p = .01$ are 0.444 and 0.561, respectively. The odds of obtaining an accuracy level of 0.95 by chance are <0.001. The odds of obtaining such an accuracy level by chance on two or more of the 16 combinations is infinitesimal. Once again, the performance of superforecasters was clearly predicted by field independence.

4.5. Limitations and future directions

4.5.1. Statistical issues

There were some weak effects and some strong effects in the multiple regression results. The weak effects could have resulted from some Type 1 error, which would have the effect of negating some variables with small effect sizes. The counter-argument, however, is that that most of the personality variables that did enter the stepwise regression models clustered around the theme of creative personality. For both personality and cognitive variables, the results were consistent with the initial premise that the forecaster needed to consider different outcomes of the chaotic data series, which would require a modicum of divergent thinking. The results were also consistent with prior reports by Loye (1995), Mellers et al. (2015), and Poore et al. (2014).

The results of the study cannot be attributed to overfitting the regression models, however. The number of predictors ranged from one to five variables. With 147 participants, the number of cases per variable ranged from 29.4:1 to 147:1. These ratios are well above any reasonable lower limit that might suggest overfitting occurred.

An interesting question still remains, however, regarding why the personality traits change across forecast levels. Although there is much to be learned about the role of personality in forecasting success, we do know that multiple traits, particularly those associated with creativity, are associated with great forecasting accuracy. We also know from previous analyses (Guastello, Futch, Marcisek, Mirabito, Green, and Witty, in press) that forecasting accuracy declines with multiple forecast steps, and that the best, moderate, and poorest performers use different heuristics to make their forecasts. The shift in prediction accuracy is related to the increasing difficulty of the task and the intrinsic interest of participants in making good forecasts (Mellers et al., 2015). Thus those who make a good forecast on the second step are likely to have a personality or cognitive advantage that the less successful ones might not have.

One can put a statistical frame around the question and suggested answer by also considering the models in Table 8 in which a prior forecast accuracy, A_{T1} was used as a predictor of performance on the next forecast A_{T2}. If a personality variable X_{T1} is correlated with A_{T1}, its shared variance with A_{T1} is subsumed in A_{T1} when it is used to predict A_{T2}. Thus X_{T1} drops out of the model on the subsequent forecast. Then, because A_{T1} accounts for a substantial amount of variance in A_{T2}, residual variance in A_{T2} decreases, and a new variable X_{T2} could play a statistically significant role.

4.5.2. Personnel selection strategies

The study produced a viable strategy for selecting personnel for jobs in which forecasting was a prominent component of the work. If one takes effect size and the number of times in which a particular variable appeared in the regression models into account, there were two robust predictors of success, field independence and self-sufficiency.

The effect size for field independence in the six cases where it occurred for three out of four attractors ranged from 3.0% of performance variance accounted for to 4.8%. Field independence did not have any impact on performance on the Lorenz attractor, however. Nonetheless, the odds of a variable with an alpha level of 0.05 appearing in six out of 16 regression models is 0.0001.

The second prominent variable was self-sufficiency. It only occurred on the Lorenz attractor, where its effect size ranged from 4.3% to 5.7% of variance accounted for. The odds of a variable with an alpha level of 0.05 appearing in four out of 16 regression models is 0.0061.

Although effect sizes in this range are considered “small,” they can have a strong practical impact on personnel selection decisions to the extent that the base rates of success and the selection ratio are both low, and the applicant can be selected from the top predicted-performers in the applicant pool (Guion, 1998). The base rates of forecasting accuracy in the present study varied substantially by attractor type.

The practical value of the two variables is most prominent in on the first forecast. Referring to Table 8, the effect sizes of all personality and cognitive variables ranged from 3 to 9% of variance accounted for on the first forecast. After that, the effect of personality and cognitive variables beyond knowledge of the accuracy of the first forecast dwindled. Thus if one wanted to produce a personnel selection strategy on the basis of these results, the emphasis should be placed on determining who makes a good first forecast. The prediction of subsequent performance then depends on the accuracy of prior forecasts.

This study investigated a generic form of chaotic-forecasting ability using number series that were produced by known chaotic attractors and decontextualized from any one situation or domain of knowledge. It is thus uncertain whether individual differences chaotic-forecasting ability could differ across contexts, or whether they could be consistent across contexts. Although the role of domain specific knowledge in chaotic-forecasting is uncertain at present, numerical studies (Hommes & Rosser, 2001; Sorger, 1998) and indicate that it could be profound. Another related outstanding question is how forecasters choose between a stochastic versus deterministic strategy when approaching a new forecasting challenge.

4.5.3. Substantive issues

Although meteorology, economics, and politics are good places to find forecasting problems, skill at forecasting chaotic events would be of value wherever dynamic situation awareness (Chiappe et al., 2015), or complex systems is required are operating. Situation awareness occurs at three cognitive levels: (a) acquiring accurate knowledge of the present state of the system, (b) accurately forecasting what the system would do next under present conditions, and (c) accurately forecasting what control actions would affect the outcomes of the system (or not).

Situation awareness is typically bolstered by visual displays of information with the further objective of providing the human decision makers with the information they need and not clutter the displays with information that they do not need. The absence of visual displays is likely to place a greater demand on working memory than what was required in the present study. Visual displays of questionable quality are likely to require stronger field independence to isolate the information that actually matters.

If the information search is novel, divergent thinking and creative personality traits would be instrumental in finding and organizing information that would produce the desired forecast. The trait self-sufficiency (Q2+) would be critical to forecasters who are acting alone. It could play a different role when the forecasts are made by a team. Self-sufficient people are self-reliant, resourceful, and are not likely to “follow the crowd” (Cattell et al., 1970; Sternberg & Lubart, 1995). If they are also experimentive and open to change (Q1+) – another trait from the creative profile – they could be convinced to change views if the supporting rationale was rigorous enough. Sometimes a forecaster takes an approach that deviates from the group's usual strategy and arrives at a more accurate forecast (Hoffman et al., 2017).

Finally, further research could continue from the stream of dynamic decision studies wherein participants' forecasts and control actions affect the state of the managed system (Osman, 2010). It would be helpful to know the level of chaos in those simulations of complex system behavior and observe the patterns of performance accuracies over time. Historically, it has been difficult to predict the best performers in a dynamical decision set because of the contingency of one decision on the next. The present study offers a statistical strategy for doing so.

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The majority of the writing was done by the first author (Guastello).

Declaration of competing interest

None.

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