Attitude to Risk Questionnaire

Due Diligence

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1 Executive Summary

This report summarises the steps followed by the Henley Business School, University of Reading research team, in developing an attitude to risk questionnaire (ATRQ) for Dynamic Planner. The process initially began in September 2016 and was completed in September 2017. The ATRQ comprises a set of 15 questions.

The ATRQ is built upon strong theoretical foundations in psychometrics and attitude measurement. As such, it addresses two aspects important when assessing attitudes to risk for accumulation and decumulation: the *content* and the *structure* of the attitude to risk. The *content aspect* classifies questions as drivers, constrainers, and enablers of risk attitude, where different psychological factors are assessed to establish what motivates, prevents, and enables risk-taking behaviour. In terms of *structure*, each question is worded to also reflect either a behavioural, cognitive, or emotional manifestation of risk. The composite attitude to risk (ATR) scale is therefore made up of a balance of questions that together represent the content and structure of ATR in line with best practice and is suitable for clients. Inconsistency flags minimise the likelihood that a disagreement between the client response from one specific question and the overall outcome would leave the advisor exposed to potential claims that the selected investment proposition contradicts the client's revealed preferences.

During development, the ATRQ was subjected to several rounds of testing with both experts (independent financial advisors and Dynamic Planner staff) and a sample of over 800 profiled respondents, followed by another round of testing with a further 1,000 respondents. In 2024, it is now completed by over 310,000 clients per year and this data is regularly analysed to assess the validity and reliability of the ATRQ. Based on recent analysis, an updated model is included here. The model does not lead to a change in the questions or scoring mechanism but will allow advisers and clients to have greater insights into the psychological factors that drive a client's attitude to risk.

The Dynamic Planner 15 Question psychometric risk profiling questionnaire was developed by Chris Brooks, Carola Hillenbrand and Kevin Money at Henley Business School, University of Reading and must not be reproduced without permission.

2 Background and Motivation

Dynamic Planner offers an attitude to risk questionnaire (ATRQ) based on psychometric testing principles as part of its Dynamic Planner risk profiling and financial planning system. The system is set up to “flag” situations where the response to specific questions is at variance with the calculated attitude to risk (ATR), or where the number of middle answers (“Neither agree or disagree” [sic]) is high, suggesting a lack of engagement with the questionnaire, so that financial advisors are aware of the inconsistency and can probe it further with their client.

The client then also separately answers questions regarding their level of investment experience and five further questions that measure their capacity to bear losses. These questions are not scored but are designed to facilitate a dialogue between client and advisor, to allow the advisor to assess these factors. Following this process and discussions between the client and advisor, they will arrive at an agreed risk profile (the “selected risk profile”).

In building the ATRQ, Dynamic Planner wished to improve upon existing questionnaires, reflecting and responding to user feedback since they were originally released to:

- Reduce occurrences of direct questions relating to specific investment choices (e.g. a preference to put money in a bank account). We term these “killer questions”, due to their bluntness.
- Reduce questions which are often seen as a test of financial knowledge, rather than pure attitude.
- Reduce questions which ask the client to compare themselves to their peers.
- Reduce the redundancy in the questions – several of the existing questions seem repetitious.
- Reduce inconsistencies between questions. Some of these questions are consistently flagged from the same direction (consistently higher or lower than the other questionnaire responses). This can be a sign of a question with a bias towards the high/low end of the risk tolerance spectrum.
- Incorporate developments in psychometric testing theory in the time since the questionnaires were developed.

Based on this, Dynamic Planner commissioned Henley Business School, University of Reading to construct an ATRQ. The brief was to retain the desirable features that are present in the existing questionnaire, but in addition it should:

- Contain only new questions to make use of new developments in psychometric testing theory.
- Have a robust theoretical underpinning that is well rooted in the psychology of financial decision making and using sound psychometric principles.
- Cover a range of dimensions of perceptions of risk.
- Make clear the fundamental trade-offs between safety and potential returns.
- Be supported by the whole range of stakeholder groups.
- Be validated with an acceptably large sample of respondents.
- Continue to adhere to FCA guidance regarding risk profiling tools by:
    - Avoiding questions which are complex or assume a high level of mathematical ability[1]
    - Avoiding questions which assume prior investment experience
    - Avoiding questions which ask two questions in one
    - Using appropriate weighting for answers[2]

[1] https://www.fca.org.uk/publication/finalised-guidance/fsa-fg11-05.pdf
[2] https://www.fca.org.uk/firms/assessing-suitability

3 Due Diligence Summary

3.1 What does this questionnaire do?

The Dynamic Planner 15 Question Attitude to Risk questionnaire is a tool to help understand the attitude to investment risk of a client seeking financial advice. It is intended to be used either as part of a broader advice process, or online guidance to place the individual on the Dynamic Planner risk scale from 1 to 10.

3.2 Who designed the questionnaire?

The questionnaire was designed by academics at the Henley Business School, part of The University of Reading:
Professor Chris Brooks – Professor of Finance, Director of Research for the Henley Business School.
Professor Carola Hillenbrand – Professor of Organisational Psychology.
Professor Kevin Money – Professor of Reputation and Responsible Leadership.

3.3 How is the questionnaire scored?

The questionnaire is scored based on the responses provided. All responses are scored, and all questions have an equal weighting on the final score. Some questions are scored low to high, while some are scored high to low. All questions must be answered.

Dynamic Planner checks for inconsistencies in the client's responses in two ways. Firstly, if too many middle answers are selected these are highlighted for the adviser to discuss with the client. Secondly, there are flags if any individual question is answered in a way which seems inconsistent with the way in which the rest of the questions have been answered.

3.4 How has the questionnaire been tested?

The questionnaire was tested with over 1,800 individuals prior to its general availability in Dynamic Planner. Respondents were selected to match the broad demographics of clients advised through Dynamic Planner. In 2024, the questionnaire is completed by an average of 26k clients per month and this data is regularly analysed to test the questionnaire and the model which underpins it.

For full details of the testing please see sections 6-8 of this document.

3.5 What limitations do questionnaires have?

The questionnaire only measures an individual's attitude to risk. Other factors should be considered when selecting a suitable risk profile for an individual, such as their knowledge and experience, capacity for taking risk, sustainability preferences, vulnerabilities, and their specific objectives.

Dynamic Planner implements an inconsistency check as part of the risk profiling process, but care should be taken to address any other inconsistencies that may exist within the client's responses, or indeed the client's responses compared to their financial partner (if any).

Where the questions are answered in the presence of an adviser, it is possible that they could unduly influence the responses of the client. Where two individuals are responding to the questionnaire, it is possible that one individual is dominating the responses of the other.

4 Theoretical underpinning

4.1 Establishing a theoretical background

In this section, we present evidence from the academic literature that provides the theoretical underpinnings for the development of the ATRQ. In this regard, a sensible starting point is to consider whether an attitude to risk questionnaire is actually the most appropriate tool to elicit risk preferences from clients. While several methods exist for this purpose, there is broad support for the attitude to risk questionnaire approach given its objectivity compared with more informal techniques (MacCrimmon & Wehrung, 1986) and its relative simplicity. Questionnaires have also received regulatory support, with the Financial Services Authority reporting in 2011 that "Where they are used within a suitability assessment process, tools and questionnaires can help to provide structure and promote consistency and so can usefully support the discussion a customer has with their adviser or investment manager".[3] If appropriately designed, a major benefit of questionnaires is the lack of need for the sort of complex terminology that would be required to implement, for example, the multiple price list approach or its variants (Charness et al., 2013). Reassuringly, however, research also shows that the outcomes from these two core approaches (questionnaires versus lottery-type experiments) are closely aligned (Faff et al., 2006).

A further possibility would be to elicit information on people's risk taking in other (non-financial) aspects of their lives, which would have the advantage that the questions are likely to resonate much more with those respondents, and then to infer the same appetite for risk in the investment arena. However, academic research indicates that risk appetites are domain-specific so that, for example, risk taking in leisure activities (e.g. binge drinking or bungee jumping) will not necessarily translate into a willingness to tolerate risks in the financial context (e.g., Dreber et al., 2011; MacCrimmon & Wehrung, 1990).

A full and complete assessment of an individual's risk appetite across a variety of situations can be obtained using the "DOSPERT" (domain-specific risk taking) scale, proposed by Weber et al. (2002) which incorporates 40 questions on a range of lifestyle variables including health, social, gambling, financial and recreational risk-taking. The inconsistency of risk preferences across these categories for given individuals has been shown by Hanoch et al. (2006), amongst others.

A core purpose of developing the ATRQ was to broaden the purview of the questions asked in order to try to better capture the underlying biopsychosocial factors that affect willingness to tolerate financial risks and thus develop a questionnaire that better measures this for the whole range of clients whatever their demographic background.

[3] Financial Services Authority Finalised guidance - Assessing suitability: Establishing the risk a customer is willing and able to take and making a suitable investment selection, March 2011

While there is no widely accepted list of dimensions of risk that the design of an ATR questionnaire could be built upon, the academic literature nonetheless outlines several important areas. A good starting point is the seminal study of psychometric questionnaire design by Grable and Lytton (1999, p. 167), which is the foundation of many more recent contributions in this area.[4] Grable and Lytton (1999, p.173) identify eight dimensions of financial risk that are assessed by psychometric questionnaires:

- Guaranteed outcomes versus gambles – how much additional expected return an investor requires to give up a certain outcome in exchange for a lottery.
- General risk choice – Grable and Lytton identify this as related to the anxiety some individuals experience when faced with financial decisions.
- Choice between a sure loss and a sure gain, where participants compare alternatives that involve either a certain gain or a certain loss, which can capture loss aversion.
- Risk as experience and knowledge – captures the tendency for those with experience of investing and who are knowledgeable about it to be more risk tolerant.
- Risk as a level of comfort – this is argued to capture the extent to which individuals feel relaxed about taking risks, related to deep-seated psychological traits.
- Speculative risk – how willing participants are to speculate in situations where it may be possible to trade higher potential returns for a more certain but lower expected return payoff.
- Prospect theory – the idea that investors evaluate the performance of an investment relative to a specific reference point, and may view gains and losses asymmetrically.
- Investment risk – a composite term capturing whether an individual has "the knowledge and temperament to … deal successfully with emotional investments".

Clearly, these classifications are overlapping and the psychology literature has moved on somewhat since their writing. Nonetheless, this early study provides several key ingredients that must be present in a reliable and valid risk profiling questionnaire, which we expand upon below. Risk capacity and investment time-horizon are also highly relevant factors for determining appropriate investment products for clients, but the regulatory framework states that these should be considered separately from risk appetite.[5] Similarly, financial knowledge is also important but considered in a separate set of questions within Dynamic Planner's current process and therefore the ATRQ exclusively focuses on risk tolerance, measured in the form of attitudes.

The core purpose of ATR surveys is, as the label suggests, to measure the client's ***attitude*** to financial risks. Attitude measurement has a long history in psychological theory with well-established knowledge relating to attitude origin, nature and manifestation (Ajzen & Fishbein 1977; Breckler 1984; Cooke & Sheeran 2004; Glanz, Rimer & Viswanath 2015). Summarising this body of knowledge, many scholars would probably agree that the measurement of attitudes requires the researchers to define the ***content*** of the attitude measurement (i.e. what content aspect of an attitude is being measured, for example an attitude aimed at achieving gains or an attitude aimed at avoiding losses), as well as the ***structure*** of the attitude measurement (i.e. how is the attitude expressed or manifested in the life of the respondent, for example as a cognitive thought or as an affective emotion).

[4] Interestingly, this original study recommends that Cronbach's alpha estimates should be of the order of 0.5 to 0.8, which is below the corresponding figures exhibited by the current DT question body.
[5] See, for example, the Financial Conduct Authority's *Conduct of Business Sourcebook* (Chapter 9 on suitability) for the relevant UK legislation. The FSA's "Finalised Guidance" report (op. cit) terms this "conflation risk" and uses "tools that conflated pieces of information relating to the wider suitability assessment and the risk a customer is willing and able to take into a single automated output" as an example of poor practice.

In terms of ***attitude content measurement***, we build on a model that explores attitude content in terms of drivers, constrainers and enablers (Dulewicz & Higgs 2000), which is described in more detail on the following pages. In terms of ***attitude structure measurement***, we build on a model that explores attitude structure in terms of emotional, behavioural and cognitive elements, sometimes referred to as ABC model of attitude by industry and practitioners.[6] Note that the terms 'affective' and 'emotional' are used interchangeably in the psychology literature but we will stick to the latter in the remainder of this report as it is likely to be more familiar to our intended audience. *The **content and structure of attitude to risk*** could therefore be classified in a 3x3 grid as in Table 1:

Attitude to Risk	Attitude Structure: **Affective / emotional (A)**	Attitude Structure: **Behavioural (B)**	Attitude Structure: **Cognitive (C)**
Attitude Content: **Drivers (DR)**	Emotional drivers to take risk (e.g. feelings of excitement, thrill, positive anticipation)	Behavioural drivers to take risk (e.g. expression of past risk-taking behaviour and desire to engage in risk behaviour in the future)	Cognitive drivers to take risk (e.g. positive beliefs about risk outcome, cognitive ease with uncertainty; a desire for big gains)
Attitude Content: **Constrainers** (CON)	Emotional constrainers to take risk (e.g. feelings of anxiety, fear, sense of caution)	Behavioural constrainers to take risk (e.g. behavioural expression of risk-avoiding behaviours)	Cognitive constrainers to take risk (e.g. negative assessment of the utility of risk outcome, negative beliefs about cognitive uncertainty, preference of certainty over risk)
Attitude Content: **Enablers (EN)**	Emotional enablers to take risk (e.g. a sense of emotionally supportive circumstances)	Behavioural enablers to take risk (e.g. expression of behavioural coping mechanisms)	Cognitive enablers to take risk (e.g. beliefs of supportive environmental factors, skill-sets or other enabling conditions)

Table 1: Content and Structure of Attitude to Risk Measures

[6] See http://study.com/academy/lesson/the-abc-model-of-attitudes-affect-behavior-cognition.html.

In terms of the ***content*** of attitude to risk measurement, we build on the work of Dulewicz and Higgs (2000), who suggest that dynamic and complex attitudes can be measured in terms of drivers, constrainers and enablers. We propose that it will also be useful to measure attitudes to financial risk in a similar way. As such, we categorise content aspects of financial risk attitudes outlined in the literature above as drivers, constrainers and enablers and propose a dynamic model of financial risk attitude. This can be used to calculate an overall risk score – but can also usefully capture the dynamic nature of risk in terms of three aspects, as shown in Figure 1.

- **Drivers:** The reasons for engaging in risk-taking behaviours – these include underlying motivations for a desired end state (which may include the acquisition of material goods, the establishment of relationships, gaining knowledge/insight as well as defending what is already possessed or aspirations versus contentment with what they already have). Other relevant drivers may include how serious is a shortfall from the desired outcome (e.g. paying children's university fees versus buying a yacht).

- **Constrainers:** These are the person-based factors that may hold back or enhance the impact of the drivers of risk behaviour. They may include personality factors, emotional pre-disposition and the locus of control (making sense of outcomes), and attitude to change: if people find it difficult to give up what they have at the moment, then may want to take less risk. In particular, we will include questions which measure aspects such as anxiety and emotional stability. These are typically unchanging and deep-seated characteristics such as whether a person is calm or prone to stress, and cannot be changed easily.

- **Enablers:** The circumstantial and environmentally based factors that could enable risk-related behaviours. These factors are less about stable internal personality characteristics and more subject to change. They include the knowledge, skill and overall circumstance of the individual when it comes to risk, which can enhance emotional intelligence. Enablers can be more easily modified than the other two factors, but knowledge and circumstances (capacity, liquidity and timeframe, for example) are measured separately from attitude to risk in the Dynamic Planner process and therefore we do not consider them further in the development of the ATRQ.

Importantly, these content aspects of risk attitude can manifest at the emotional, behavioural and/or cognitive level of individuals. For example, some individuals may be driven to take risks for emotional reasons (e.g. a sense of excitement by the prospect of investing money), while others may be driven to take risks for mainly cognitive reasons (e.g. a positive cognitive assessment of the risk outcome). Likewise, some individuals may be experienced with risk-seeking behaviours in their life and thus quite comfortable with such situations, while others may find that they often back-out of actual risk-seeking behaviour despite perhaps some cognitive attraction to the idea of investing.

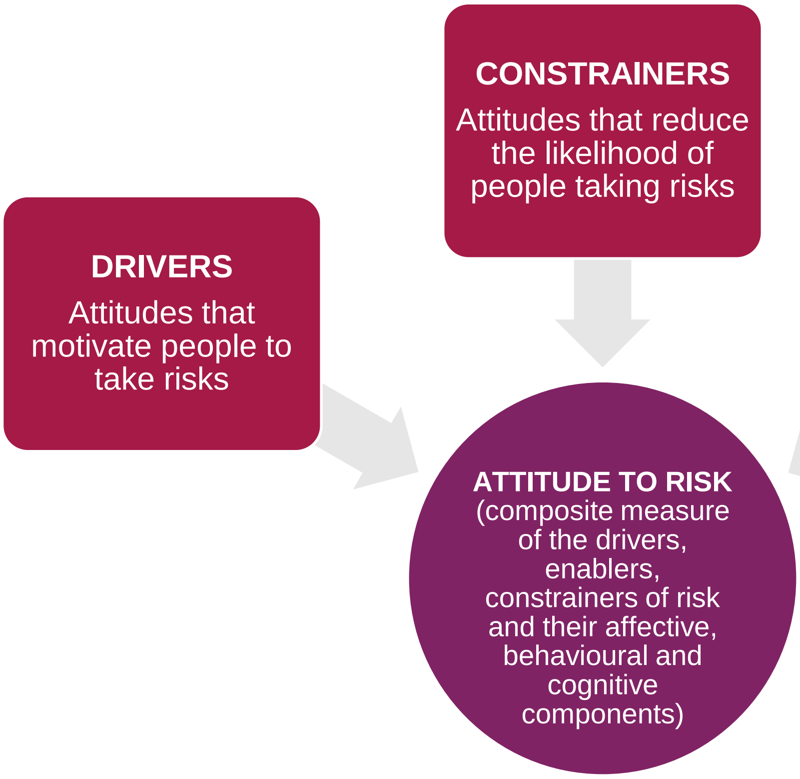

Figure 1: The Drivers, Constrainers and Enablers Framework for the Content Dimension of ATR

It should be noted at this point that it is not required that an attitude measure contains equal assessments of all the 3x3 dimensions shown in Table 1 in practice. Some attitudinal dimensions may be easier measured through behavioural indicators, while others may be best explored through cognitive assessment. For example, retail investors may experience constraining factors to be related to their specific circumstances, which they may need to assess cognitively, and as such measurement of constrainers can usefully be linked to cognitive and behavioural aspects of risk attitude. In our development of the attitude to risk measure, the researchers ensured that elements relating to drivers, constrainers and enablers were represented, and measurements were situated at the emotional, behavioural and cognitive levels, but the exact combination of these aspects was not restricted to equal numbers, but rather adopted based on statistical analysis presented in sections 6-8 and the context to provide the most appropriate structure to measure the various content dimensions.

Expanding some of the ideas outlined in 1-3 of ***attitude content*** above with aspects of affective, behavioural or cognitive ***attitude structure***, the literature has suggested that emotional or "soft" skills are equally as important as cognitive skills in determining the results from decisions (Heckman et al., 2006) and hence personality plays a key role in influencing the way that financial choices are made. One way to classify personality traits is along the "big five" dimensions developed by Costa and McRae (1992), namely: openness to experience, conscientiousness, extraversion, agreeableness and neuroticism. Brown and Taylor (2014) test this taxonomy of personality characteristics using financial data from the British Household Panel Survey and find some of them, notably extroversion and conscientiousness, to be related to the propensity to build up debts.

4.2 Literature review

As highlighted in section 3, there are three factors to consider regarding attitude content; what motivates people to take risk (drivers), the personal characteristics that may prevent people from taking risk (constrainers), and the environmental factors that may enable risk-raking behaviours (enablers). Some psychological factors that affect what drives, prevents, and enables people to take risk have been discussed, but there are others to consider when developing an ATRQ.A further possibility would be to elicit information on people's risk taking in other (non-financial) aspects of their lives, which would have the advantage that the questions are likely to resonate much more with those respondents, and then to infer the same appetite for risk in the investment arena. However, academic research indicates that risk appetites are domain-specific so that, for example, risk taking in leisure activities (e.g. binge drinking or bungee jumping) will not necessarily translate into a willingness to tolerate risks in the financial context (e.g., Dreber et al., 2011; MacCrimmon & Wehrung, 1990).

4.2.1 Emotions towards investing

There is substantial evidence that people's tendencies to experience specific emotional states will affect their investment decisions. The "risk as feelings" hypothesis suggests that reactions to risks faced may not be the result of a cognitive process, but rather result from emotions (Loewenstein et al., 2001). For example, anger is linked with a willingness to invest in riskier portfolios while those who are anxious will select low risk portfolios or may avoid investing altogether and will be quick to close out positions that have either gained or lost money (Gambetti & Giusberti, 2012). Anxious investors tend to dwell on previous losses (Smith & Ellsworth, 1985), while those with a predisposition to anger have more of an internal reference point and consider circumstances to be forecastable and low-risk (Ellsworth et al., 2003). Similarly, those with a tendency to depression or hopelessness are more likely to build up debts and to save less in pensions (Brown, 2011), and individuals with low self-esteem are likely to be more risk averse (Judge et al., 1999), while those who have strong confidence in their own decision-making abilities are generally more risk tolerant (Krueger & Dickson, 1994).

It is often suggested in the literature that emotions interfere and prevent us from making rational choices and lead us to make mistakes (Baker & Nosfinger, 2002; Lo et al., 2005; Rubaltelli et al., 2015), investors with low self-control and difficulty with regulating their emotions in a healthy way may hold on to losing stocks to avoid negative emotions and sell winning stocks to feel immediate positive emotions (Shefrin & Statman, 1985), however emotions can also be used and harnessed to help solve problems and make decisions by providing information about the quality of decisions we have made or as feedback to help evaluate future choices (Rubaltelli et al., 2015; Ackley, 2016; O'Connor et al., 2019).

In terms of emotional intelligence, which refers to an individual's ability to accurately interpret and perceive emotions, to express their emotions and use them to facilitate various cognitive activities, such as thinking and problem solving, it has a direct relationship on investment decisions. Dhiman & Raheja (2018) found emotional intelligence has a stronger influence on risk tolerance than personality traits, particularly investors self-awareness of how they are feeling, ability to handle their emotions and motivate themselves to achieve their goals relate to their abilities to tolerate risks.

4.2.2 Locus of control

Also, under catalysts and constrainers, the locus of control is an important idea in psychology that different people have different ways to rationalise realised outcomes as being either a product of their own choices and actions, or due to external forces beyond their control such as luck, other individuals, or divine intervention. Those who attribute success or failure to their own efforts are said to have an internal locus of control but those attributing it to outside factors have an external locus reference point. The locus of control is a key concept that is relevant here not only because it has been found to be a major determinant of economic outcomes such as earnings and unemployment (Goldsmith et al., 1997; Osborne Groves, 2005), but also because it relates to an individual's resilience in coping with unanticipated occurrences such as health shocks.

Research shows that the locus of control is highly stable over time, as are risk tolerances, except among the very young or very old. This stability holds even in the face of severe exogenous events such as the death of a partner (Cobb-Clark & Schurer, 2013) and also in the face of significant economic shocks such as the global financial crisis (Gerrans et al., 2015). Those with a more internal reference have stronger self-control mechanisms (Rosenbaum, 1980), are more likely to create wealth and to hold financial assets (Chaterjee et al., 2011). Therefore, there is a tendency for households with an internal locus to save more, both in absolute terms and as a proportion of their incomes (Cobb-Clark et al., 2013). Those with an external locus are therefore a “sensible target group for intervention” (Cobb-Clark et al., 2013), i.e., they may need more care and support in their decision-making, and are also more likely to blame others, including a financial advisor, if things go wrong.

4.2.3 Anticipated regret

There is also evidence that decisions are made not only as a result of the feelings that they elicit immediately, but also on the basis of the emotions that the person anticipates they may feel after they have made them. One such emotion is regret, which may be defined as an emotion whereby an individual assesses that their current circumstances could have turned out better had they made a different choice or acted differently in the past. Regret is a stronger emotion than disappointment, and in the investment arena the client feels a sense of responsibility in a regret situation, and indeed it is so powerful that it can lead to irrational decision-making (Michenaud & Solnik, 2008). Thus, the anticipated pain of regret drives investing behaviour alongside expected payoffs (Loomes & Sugden, 1982) and can have an effect in many financial situations. For example, the fear of regret tends to lead individuals to stick with default options or existing positions.

Regret theory has proved useful in explaining a number of otherwise enigmatic decision-making outcomes, including the zero-equity holding puzzle, whereby investors hold no equities in their portfolios even in the face of attractive risk-return characteristics and diversification benefits (Barberis et al., 2006). While fear of regret may drive investor decision-making, the outcome in terms of whether risk taking is enhanced or diminished is in general ambiguous and may therefore be time-varying, although demand for insurance is likely to be increased (Muermann et al., 2006). Regret may be felt if an investor has taken insufficient risk during an equity bull market for example, when the portfolio relatively underperforms, or when the markets are performing poorly, and the investor has large exposures which with hindsight they wished they had closed out earlier.

4.2.4 Fear-of-missing-out

Similarly, the fear-of-missing-out (FOMO) can lead consumers to believe they are missing out on opportunities that others are not, which influences consumers decision making (Hodkinson, 2019; Dogan, 2019; Abel et al, 2016). FOMO can go beyond what other consumers may be experiencing, relating to the fear of missing out on a potentially profitable investment, and this is particularly apparent when the value of an asset increases dramatically over a short period of time (Balcilar & Ozdemir, 2023; Neumann et al., 2023).

The fear of missing out drives and motivates behaviours such as investing, particularly involving ownership of cryptocurrency, but the relationship between FOMO and investing behaviour is also influenced by financial literacy, greater knowledge increases fear, and FOMO is a significant positive predictor of risk tolerance (Gerrans et al., 2023).

The fear of missing out has also been shown to impact susceptibility to other behavioural biases that influence risk taking behaviour such as loss aversion and herding mentality (Gupta & Shrivastavam, 2022). Potsaid and Venkataraman (2022) highlight how little research has analysed FOMO as a personal trait and instead the broader impact, such as on herding behaviour. They examined investors fear of missing out when they were restricted from knowing what others were doing within the markets and found that those with greater FOMO reacted more negatively towards these restrictions.

As FOMO traditionally relates to social experiences and less so to the investment setting, although research shows the impact on financial decisions, Clor-Proell et al. (2020), designed a measure (I-FOMO) to capture investment specific fears considering the fear of missing information that could move prices. I-FOMO relates to concern for losing an opportunity where the potential reward is monetary rather than psychological well-being reward from a social experience.

The researchers state the importance of measuring fears of missing out in this context as those who place a high value on social experiences may not necessarily place such high value on monetary experiences, and vice versa.

4.2.5 Risk-taking identity

Our self-identity also influences how we intend to behave and our actions (Holland et al., 2009). Our identity can involve personal aspects that make us unique, or social aspects that are intrinsically rooted in different groups and cultures we are a part of (Oyserman & Destin, 2010). There is considerable evidence demonstrating that we are driven and motivated to behave in ways that reflect our self-identity, our sense of who we are (Mills & Pawson, 2012; Hamilton, 2006; Phillips & Hayes, 2006).

The theory of planned behaviour has contributed significantly to understanding the drivers of human behaviour and illustrates the importance of attitudes, subjective norms and perceived behavioural control on behavioural intentions and actual conduct, as such factors are potential explanations for why attitudes do not translate into behaviour (Ajzen, 1985;1991; Juvan & Dolnicar, 2014). All factors of the model have been independently shown to influence investment intentions, such as plans to purchase shares, as well as levels of risk tolerance (Alleyne & Broome, 2011), however evidence from Dean et al (2012) also shows that adding self-identity to this model informs the prediction of intentions to behave beyond the existing variables. Understanding how an individual identifies with risk-taking behaviour and their self-perceptions provides great insight into how they would intend to behave during their investment journey.

4.2.6 Preference for certainty

Kahneman and Tversky (1979) coined the certainty effect which explains that in relation to gains, people overweight certainty and therefore prefer to choose a sure or certain gain over a risky one. Interestingly, in contrast, people prefer not to accept a sure loss over a risky loss (Mather et al., 2012). This preference for certainty is reflected in the shape of the utility function under prospect theory which argues that people prefer more certain gains rather than the prospect of larger gains if this involves taking more risk.

A large body of research has shown that within difference choice contexts there is this strong preference for certainty (Duke et al., 2018; Chavali & Mohanraj, 2016). Çera et al., (2021) found a negative relationship between avoidance of uncertainty and financial risk tolerance. Risk averse investors have a preference for certainty which may be due to their aversion to experiencing loss or their difficulty to tolerate the ups and downs which may be required to make greater returns.

Loss aversion is another important concept associated with prospect theory where “losses loom larger than gains” (Kahneman & Tversky, 1979). The pain of losing is psychologically around 1.5 to 2.5 times as powerful as the pleasure of gaining and therefore people are more willing to take risks (Schindler & Pfattheicher, 2017). Researchers have found that those with low risk tolerance and a conservative personality are subject to loss aversion biases. Similarly, loss aversion affects risk tolerance with investors who have a greater desire to avoid loss being more risk averse (Arora & Kumari, 2015; Dickason & Ferreira, 2018). The large body of research into loss aversion and prospect theory supports why risk tolerance questions based on loss aversion are relevant and should be incorporated into an assessment when determining portfolio allocation (Guillemette et al., 2012).

4.2.7 Uncertainty tolerance

Despite investors being fully aware that no investment is completely risk-free, and certainty is something very difficult to experience in many areas of our lives, they still often have a strong desire for certainty. However, this desire does not explain an individual’s ability to tolerate uncertainty and manage their emotions during challenging periods.

Risk tolerance is based on the degree of uncertainty that an investor can handle, and therefore even risk tolerant investors are not immune to negative reactions. However, questionnaires examining attitudes to risk can often neglect the emotional elements of risk tolerance and being able to handle the uncertainty within the market. When people are intolerant of uncertainty, they don’t like to be in situations where there is ambiguity about what will happen in the future, which would cause them to feel anxious (Buhr & Dugas, 2009).

Intolerance of uncertainty is germane to attitude to risk, and it is highly negatively correlated with the tendency to purchase risky assets and participate in the stock market (Conlin et al., 2015). Interestingly, no relationship between ambiguity tolerance and financial risk tolerance was found by Wong and Carducci (2013), but as they mentioned, the ability to tolerate uncertainty associated to financial risks may differ from generalised abilities to tolerate ambiguity. Brooks and Williams (2022) found that those with a high level of intolerance to uncertainty were more likely to sell their investments during a period of volatility. These individuals might fear the unknown and therefore be prone to make rash and self-defeating decisions requiring more guidance and time to reflect and regulate their emotions.

4.3 Summary

The three dimensions (drivers, catalysts/constrainers, and enablers) will work together to form an overall picture of financial risk tolerance which incorporates general attitudes to risk, change and emotional resilience to withstand losses. Thus, the aggregate score will be a composite of all of these factors which may work in unison or may conflict to some extent. The framework recognises that attitudes to complex criteria are not always congruent, and thus it is useful to unpack the attitude into different aspects. For example, a decision maker may wish to act in an emotionally intelligent way but may not have the emotional control or skill.

We believe that this framework constitutes an intuitive way to categorise some complex thinking in a model that could help advisors and clients completing the questionnaire too. A further benefit of adopting a structure such as this to support questionnaire design is that it will allow us to glean useful information about why a particular outcome may have occurred and whether it is likely to be stable over time.

In summary, the approach that is utilised to measure risk attitude in this study provides information about two aspects important for attitude measurement: the *content* and the *structure* of the attitude to risk. The *content aspect* classifies questions as drivers, constrainers and enablers of risk attitude. In terms of *structure*, each question is, at the same time as describing a content-dimension, worded to either describe whether an attitude is manifested at a behavioural, cognitive, or emotional level.

Finally, there are practical aspects to consider when developing an attitude to risk measure for us in practice, such as: How long should an ideal ATR questionnaire be? There is ample evidence to suggest that multi-item questionnaires provide more accurate risk appetite assessments than those based on a single question (e.g. Roszkowski & Snelbecker, 1989), with the answers then aggregated together. Extending this argument, all else equal, more items will reduce measurement error, but one must be mindful of the issues of question fatigue and lack of focus if the survey is too long (Roszkowski & Bean, 1990). In other words, longer questionnaires will perhaps be more accurate but there is a danger that boredom will set in among some respondents so that they cease to pay sufficient attention to the process. These would also take up more time during meetings and the advisors that we spoke to suggested they would prefer the risk profiling part of the discussion to take no more than 10-15 minutes.

In addition, the questions should be designed to minimise the potential for any "perceptive or cognitive distortions as highlighted by behavioural finance" (Linciano & Soccorso, 2012) – in other words, they should be in clear, non-technical language and care taken to avoid behavioural biases affecting the outcomes, such as framing effects or the chance that the respondent will anchor on an initial level of wealth. The following section will describe in detail the process that was followed to develop the ATRQ measure based on best questionnaire development practice.

5 Drawing Up a Long-list of Candidate Questions

In line with best academic practice, a "long-list" of approximately 50 candidate questions was developed to capture the various risk-related attitudes and both content and structure dimensions reviewed in Stage 1 above. This ensured that the questionnaire would have a robust theoretical underpinning and would cover a range of dimensions of perceptions of risk. The construction of a list of candidate questions was undertaken by the Henley Business School researchers, guided with reference to Rossiter (2002) and Summers (2001), two seminal pieces in the literature on scale (i.e. questionnaire) development. Potential questions were developed by the researchers through a brainstorming approach based on their collective knowledge of the literature on psychometric testing and risk tolerance and based on their experience of working with investment professionals and financial advisors.

We also employed two early-stage focus groups (run by the researchers) to support the development of potential questions and the refinement of their wording: one comprising only relevant Dynamic Planner staff and the other comprising a hand-selected group of supportive and engaged financial advisors.

The first of these expert focus groups involved relevant staff from Dynamic Planner, comprising staff engaged in sales, quantitative analysis, advisor liaison and a member of the senior management committee. The focus group was organised around two parts – the first ensured that all participants came to a common and shared understanding of the strengths and weaknesses of the previously used ATRQ, and the second involved a presentation and discussion of the long list of potential questions.

The second expert focus group comprised a selected group of independent financial advisors from around the UK who are current users of the Dynamic Planner risk profiling process and who are therefore familiar with its strengths and weaknesses. There was general support for the development of a broader range of question types than had previously existed, linking with measures of resilience and emotions when faced with losses in addition to introducing new questions of the more standard questions assessing attitude to risk that are already incorporated.

In addition to the general principles of good questionnaire design highlighted above, the focus group revealed a number of important insights from those at Dynamic Planner with inside knowledge of the financial advice process and the kinds of language and terminology that are likely to be appropriate for a diverse clientele. For example, the group expressed a view that the questionnaire should:

- Avoid direct comparisons with past behaviour since these would be inappropriate for first-time investors or those whose circumstances have substantively changed.
- Avoid words with negative connotations which some respondents might feel uncomfortable in selecting even if they apply, such as "reckless" or "gambler".
- Also avoid words which suggest that someone (either the client or the advisor) is at fault if investments don't pay off as expected – e.g. "blame" or "anger".
- Avoid questions or responses that the client could find insulting and therefore avoid selecting even if most appropriate, e.g. "I find investing complicated".
- Ensure that each question has a specific focus across all responses – for example, not mixing feelings about risk with the frequency of undertaking them.
- Avoid mentioning long-term futures as this may not resonate with older clients (around 10% of respondents are over 75).
- Ensure that questions do not appear to offer a "free lunch", such as "I prefer to take less risk"; instead, a question that embodies the trade-off more explicitly would be preferable, such as "I prefer to take less risk even if it means sacrificing some of the potential to make money".
- Avoid questions that stray explicitly into capacity for risk or investment experience as these belong in other parts of the process – e.g. "It would not concern me if financial risks did not pay off" may encourage clients to think about whether they have the wherewithal to absorb a loss rather than whether they have the appetite for risk.

- Avoid questions containing numerical illustrations or percentages and ensure that no financial knowledge was required to be able to fully understand the questions.

Several potential new question types were also discussed but dismissed, including:

- The addition of a sixth possible response in each case such as “None of the other responses/I don’t understand this question”, as it would be impossible to score a questionnaire with one of these responses. A Likert-type scale with an even number of responses (to remove the existence of a “Neither agree nor disagree” option) was also rejected. Such a system would force someone who didn’t understand a question to select one at random, and there would be no way to identify this. It was felt that the current methodology, in which lack of engagement can be detected and flagged without preventing the calculation of a risk score, struck the correct balance.
- Diagrams or illustrations of particular scenarios. Experience indicates that some people struggle to interpret charts or tables of numbers, and they can lead to misinterpretation. In addition, for those undertaking risk profiling via a mobile device, there is insufficient screen space to show such graphics in sufficient detail.

6 Model Development

Following the pre-testing of the questionnaire as described in the stage above, we employed a large-scale test of a reduced list of 23 questions on a representative cross-section of the expected demographic using a stratified sampling technique. The survey was undertaken online with respondents picked to meet certain quotas as discussed below. Initially a 'soft pilot' trial was run with approximately 50 respondents and then the full pilot began after ensuring the adequacy of the questions and approach in the soft pilot. Altogether, after filtering, a total of 852 responses were available for analysis from a total sample of approximately 1,000 responses.

The aim was to try to generate a test sample that replicated the likely composition of Dynamic Planner's client base as far as possible. We targeted an initial sample of 1,000 respondents and requested that the sampling frame included the following criteria:

- 50/50 gender split; 50% of respondents with at least experience of a stocks and shares ISA or other investments (not only pure savings accounts); 50% income of £50k or more; age composition of around the following: 18-39 (25%), 40-60 (50%), and 61+ (25%).
- We removed a number of obviously flawed responses (failing basic sense checks, incomplete questionnaires, selecting the same response to every question, taking less than a third of the median time to complete the questionnaire) and this left us with 852 responses.
-

We conducted several types of analysis of the survey data:

- A technique known as factor analysis
- A separate statistical evaluation of each specific question
- Correlation of each question with the overall outcome

Firstly, we employ factor analysis in order to determine whether there are a small set (<15) of (unobservable) common threads that link the questions together.

When we apply this approach using principal components analysis,[7] we are able to uncover three separate factors that together explain 61% of the variation across the questions, and separately categorise each question according to its type as a driver, constrainer or enabler of willingness to take financial risks.

Summary statistics relating to each individual question allows us to ensure that they are all working as they should and contributing sufficiently to the overall outcome. We find that for most questions the mean is close to 3, highlighting that clients are equally likely to agree as to disagree with any specific question and that there is no inherent bias in the questions that could lead to a potentially distorted range of attitude to risk profiles.

The Spearman correlations between the response to each individual question and the overall outcome were computed. For a particular question to be useful in contributing to the overall outcome, we would expect that this correlation should be above around 0.4. On the other hand, if all values were too high (close to 1), this would be suggestive that the questions were too overlapping and not sufficiently broad in scope. All correlations are within the range 0.50 to 0.83, which we conclude indicates that the questions are all contributing to the overall outcome and are relevant in assessing attitude to risk. All correlations between individual question responses and the overall calculated ATRs for all three surveys are significantly different from zero at the 1% level.

Next, we examine the Cronbach's alpha statistic. This is a measure of the extent to which the questions are on average leading to the same outcomes. Additionally, the Cronbach's alpha is a measure of internal consistency, that is, how

[7] Principal Components Analysis is a dimension-reduction tool that can be used to shrink a large set of variables to a small set that still contains most of the information in the large set. To explain, PCA is a mathematical procedure that transforms a number of correlated variables (e.g., the 15 questions) into a smaller number of uncorrelated variables (e.g., three main factors).

closely related a set of items are as a group. By construction, alpha must lie between zero and one, and its value will rise as the number of questions in the survey increases. If alpha is too low, this is suggestive that the questions are pulling in different directions, so that the overall score is in essence averaging over items that are not strongly related. On the other hand, if alpha is too high, this would be indicative of redundancy in the questions and that, effectively, the same questions are being asked repeatedly, possibly using different terminology. The Cronbach's alpha is 89.6%.

Following discussion with relevant staff at Dynamic Planner and with sight of the results from the statistical analysis following the survey, the 23 questions were narrowed down to the selected 15 questions. The wording was also examined by a professional proofreader. These steps resulted in further minor changes for clarity, but none were considered sufficiently extensive that they would undermine the validity of the survey results.

7 Model Update

Psychometric testing when developing a questionnaire allows us to explore the manner in which different populations respond to items, understand how items cluster and work together to define multiple dimensions of the variable being measured, capture which items are not relevant or are redundant, and how items impact the overall measure that is being designed. However, importantly, the developed model consisting of drivers, constrainers and enablers is able to be tested to check the validity of the factors and their associated items.

The model is regularly tested using questionnaire data received through Dynamic Planner that has been completed by advised clients. Here, we report our most recent validity and reliability tests of the attitude to risk questionnaire using data gathered from 54, 694 clients between January 2023 and May 2023.

We conducted several types of analysis:

- Exploratory and confirmatory factor analysis to examine construct validity and reliability and determine how well the existing model fits with the data
- Internal consistency to examine how items relate as a group
- Exploring individual item scores (means and standard deviations), distributions, item-total correlations, skewness, and kurtosis

Data screening	• Outliers were removed using Mahalanobis distance • Mahalanobis distance is the most widely used measure for detection of outliers when considering multiple variables as it measures the distance between a case and the distribution where larger values indicate outliers
Exploratory factor analysis (EFA)	• EFA is utilised when creating new questionnaires • Explores possible underlying factor structure and is a reduction technique • Factor extraction obtained considering varied approaches–based on eigenvalues >1; scree plot (considering point of inflexion and eigenvalues); parallel analysis (eigen values compared with the values obtained from a random dataset) • Rotation was applied to enhance the interpretability of the factor solution. Oblique (Oblimin) rotation was preferred over orthogonal rotation as it allows factors to correlate and often provides a more realistic view of the data • EFA is an iterative process- items with low loadings and cross loadings are removed to maximise the variance explained • Factors are interpreted
Internal consistency and reliability	• Measure factor reliability by examining internal consistency using Cronbach's alpha and item-total correlations • Examine how closely related a set of items are as a group
Confirmatory factor analysis (CFA): Model fit	• CFA is used to verify the factor structure- post EFA, but can be applied without EFA • CFA tests relationships between items and latent constructs • Absolute fit indices determine how well the model fits the data (construct validity)
Confirmatory factor analysis: Validity & reliability	• Construct reliability is the measure of internal consistency of each factor • Convergent validity is measured by calculating the average amount of variance captured by each construct • Discriminant validity is the degree in which one construct can discriminate between another
Descriptive statistics	• Examined to understand distributions of total score and individual item scores considering means, standard deviations, item-total correlations, skewness and kurtosis

Table 2: Summary of the purpose of each stage of the analysis

7.1 Optimal criteria

At each stage of analysis there are optimal and cut-off criteria we have referred to and considered before moving on to the following step. These are reported below and summarised in Table 3:

7.1.1 Exploratory factor analysis

The determination of the adequacy of the exploratory factor analysis (EFA) can be performed through the analysis of Bartlett's test and the Kaiser-Meyer-Olkin (KMO) measure. The KMO statistics range from 0 to 1, with values closer to 1 denoting greater adequacy of the factor analysis (KMO≥0.6 low adequacy, KMO≥0.7 medium adequacy, KMO≥0.8 high adequacy, KMO≥0.9 very high adequacy). If the result of Bartlett's test is < 0.05, factorial analysis can be used (Nievas Soriano et al., 2020). Factor loading scores greater than 0.4 are considered stable (Guadagnoli & Velicer, 1988) and it is advisable to remove any item with a communality score less than 0.2 (Child, 2006). As a general rule, the total variance explained by the retained factors should be at least 50% (Streiner, 1994).

7.1.2 Internal consistency

Regarding Cronbach's alpha, a value of 0.7 is generally agreed as an acceptable value, although 0.6 may be considered for exploratory research (Hair et al., 2014). However, a tiered approach can also be used "≥ .9 – Excellent, ≥ .8 – Good, ≥ .7 – Acceptable, ≥ .6 –questionable, ≥ .5 – Poor, and ≤ .5 – Unacceptable" (George & Mallery, 2003, p.231). For item-total correlations, the typical classification is ≥0.4 means excellent, 0.3–0.39 means good, 0.2–0.29 means marginal, ≤0.19 means poor (Qin, 2006).

7.1.3 Confirmatory factor analysis

Chi-square statistic should not be statistically significant if there is a good model fit. However, the Chi-square statistic is very sensitive to sample size and is no longer relied upon as a basis for rejection or non-rejection (Schlermelleh-Engel et al., 2003, Vandenberg, 2006). Instead, multiple model fit indices should be examined taking into account not only sample size, but also model complexity. The magnitude evaluation of RMSEA is subjective, but values under 0.08 are considered indicative of good fit and between 0.08 and 0.1 are marginally acceptable, NFI and GFI values can range from 0 to 1, and those above 0.9 are considered acceptable. TLI values typically range between 0 and 1, and values above 0.9 are considered desirable. CFI values can range between 0 for a bad model and 1 for a good model, above 0.9 is desirable. SRMR values should be below 0.08 (Awang, 2015; Nievas Soriano et al., 2020). Good construct reliability is above 0.7 and is also an indicator of convergent validity in conjunction with factor loadings being greater than 0.5 and average variance extracted (AVE) above 0.5. Discriminant validity (square root of AVE) should be higher than inter-construct correlations (Hair et al., 2014).

7.1.4 Descriptive statistics

Once items within the questionnaire are confirmed, composite scores can be calculated, and tests run to evaluate the distribution of the scores and the contribution of each item. Means should be close to 3 and standard deviations should not exceed a 2:1 ratio with any other item (Yin, 2016). Item-total correlations should be above 0.4 for each item. Skewness and Kurtosis of each item and the total should fall within acceptable ranges. This can differ dependent on the sample size, but for a large sample size (over 300), Skewness should be between +2 and -2, and Kurtosis between +7 and -7 (Kim et al., 2013).

Exploratory factor analysis	KMO>0.7
	Bartlett's test is < 0.05
	Factor loadings >0.4
	Communalities >0.2
	Total variance >0.5
Internal consistency and reliability	Cronbach's alpha >0.7
	Item-total correlations >0.4
Confirmatory factor analysis: Model fit	GFI >0.9; NFI >0.9; CFI >0.9; RMSEA <0.08; SRMR <0.08; TLI >0.9
Confirmatory factor analysis: Validity & reliability	Construct reliability (CR) >0.7
	Convergent validity (Average variance extracted (AVE)>0.5; factor loadings >0.5 & adequate CR)
	Discriminative validity (square root of AVE > inter-construct correlation)
Descriptive statistics	Means close to middle score; standard deviations not exceeding 2:1 ratio; Item-total correlations >0.4; Skewness +2 to -2 and Kurtosis +7 to -7

Table 3: Summary of optimal criteria

7.2 Data analysis

Prior to data being analysed outliers were also removed resulting in a total of 54,694 respondents. All reversed items were recoded, and the data was split for the two stages of factor analysis. Although exploratory factor analysis is not necessary at this stage, we ran this to observe whether the three factors (drivers, constrainers, and enablers) could be further explained through the model using the psychological factors we discuss in section 4. This would allow us to provide advisers and clients with greater insights into the client's financial personality.

7.2.1 Exploratory factor analysis

To determine the adequacy of running an EFA, Bartlett's test and the Kaiser-Meyer-Olkin (KMO) measure were performed. The KMO statistic was 0.93, and the result of Bartlett's test was p<0.001 showing very high adequacy and that a factor analysis can be used with this dataset. The exploratory factor analysis retained all 15 items using oblimin rotation. The EFA identified five domains based on factor loadings being greater than 0.4 and using parallel analysis fits the dataset better than the previous three factors outlined in figure 1. The five factors explain 51% of the variance in the data. Communalities range from 0.34 to 0.63.

7.2.2 Internal consistency

The reliability of the questionnaire was measured based on the internal consistency of each domain, using Cronbach's alpha and item-total correlations. Cronbach's alpha value was 0.80 for factor one (r>0.4), 0.73 for factor two(r>0.4), 0.76 (r>0.4) for factor three, 0.70 (r>0.4) for factor four, and 0.65 (r>0.4) for factor five.

7.2.3 Confirmatory factor analysis

In order to measure the construct validity of the 15-item model confirmatory factor analysis was conducted (see table 4). The model showed 87 degrees of freedom, a Chi-square value of 7140.831, and a probability level of p<0.001. The five constructs were confirmed, with the items having factor loadings from 0.55 to 0.81. A global evaluation of the model was performed to determine whether it properly replicated the existing relations; GFI (0.965), NFI (0.952), CFI (0.953) RMSEA (0.057), SRMR (0.040), TLI (0.938). These values allow us to affirm that the 15-item questionnaire previously established as five domains is a good fit, and the evaluation by the maximum likelihood estimation method was good. There is good construct reliability for all factors (CR>0.7), despite convergent validity being weaker as AVE <0.5 for factors 2, 4 and 5. This is not surprising given that there are overlaps in regard to the attitude structure of items where the five factors reflect drivers, constrainers and enablers. Despite this, if AVE is less than 0.5 but construct reliability is higher than 0.6, as it is in this case, then convergent validity of the construct is still considered to be adequate (Fornell & Larcker, 1981). The square roots of AVE for all factors are not higher than the correlation coefficients between factors suggesting that some factors are not entirely distinct from one another, which again is expected given the nature of the subset of questions and overarching themes.

		Factor loadings	Average Variance Extracted (AVE)	Errors	Construct reliability (CR)	Square root of AVE
Factor 1	Item 1	0.782	0.59	0.389	0.81	0.77
	Item 3	0.811		0.342		
	Item 15	0.715		0.488		
Factor 2	Item 2	0.778	0.47	0.395	0.73	0.69
	Item 9	0.611		0.627		
	Item 12	0.660		0.565		
Factor 3	Item 4	0.717	0.51	0.486	0.76	0.72
	Item 8	0.744		0.447		
	Item 10	0.683		0.533		
Factor 4	Item 5	0.634	0.44	0.599	0.70	0.66
	Item 6	0.686		0.530		
	Item 7	0.661		0.563		
Factor 5	Item 11	0.708	0.39	0.499	0.66	0.63
	Item 13	0.550		0.697		
	Item 14	0.610		0.628		

Table 4: Descriptive statistics of individual items.

Our latest analysis highlights that whilst our questionnaire consists of items that explore client's attitudes to what drives, constrains and enables people to take risk, there are specific psychological factors discussed in the literature section 4 which fall within these overarching themes. These factors include risk-taking identity and fear-of-missing-out which consist of questions that can explain what motivates people to take risks, for example "To achieve financial success, I would take financial risks" or "I would regret deciding not to take a risky investment opportunity if it then performed well". Often, what prevents risk-taking behaviours is associated with a fear of loss or a preference for certainty, which is a third factor highlighted in table 4. Items here, for example, state "I care more about avoiding losses than making money". The final two psychological factors are associated with attitudes that facilitate and enable people to take risks, being their uncertainty tolerance and emotions towards investing. Example items within these factors include, "If the value of my investment fell, even for a short time, it would concern me" and "Taking financial risks causes me a lot of stress" (see figure 2). This updated model allows us to understand a client's financial personality and importantly inform advisers about which elements of their personality may be driving their attitude to risk, providing a framework they can use to also justify any discussions and reasons behind adjusting the client's risk profile.

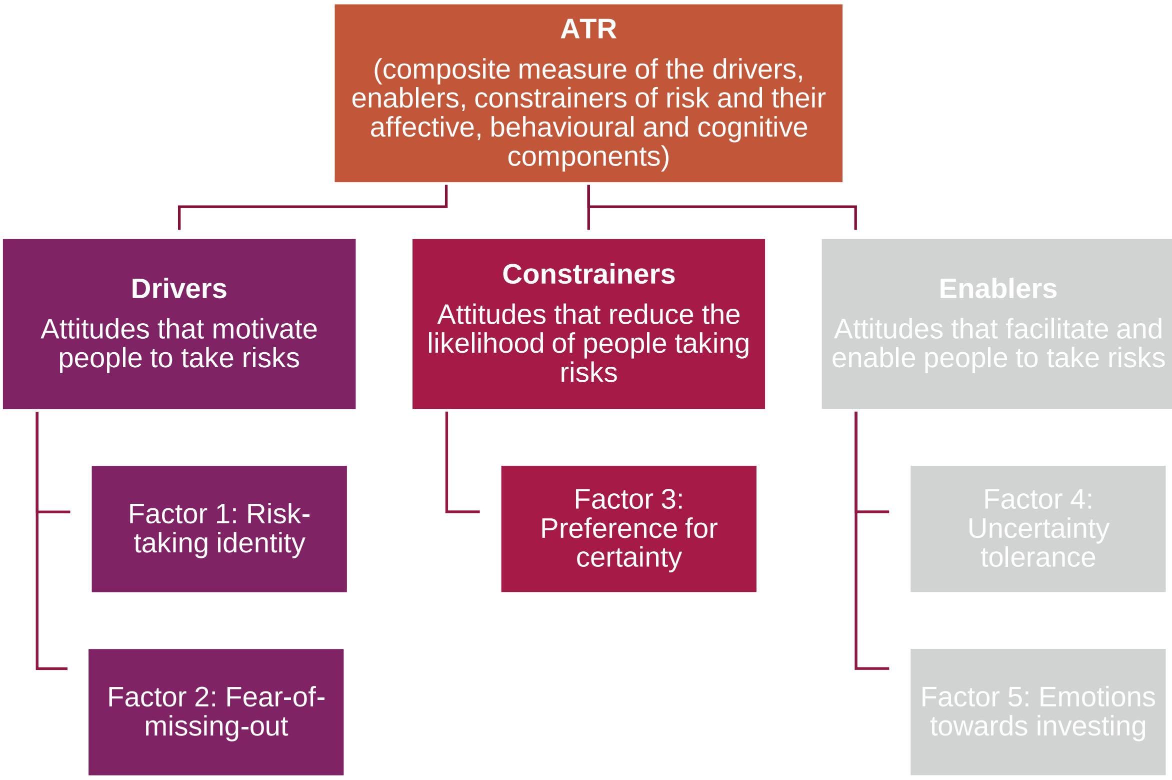

Figure 2: The Drivers, Constrainers and Enablers Framework for the Content Dimension of ATR

7.3 Analysis of individual items

Table 5 shows that there are strong positive correlations between each item and the total score which are within an acceptable range that is not only greater than 0.3, but also not too high to suggest concern about redundancy in the items (De Vaus, 2002). This further supports the validity of each item and the construct reliability of each factor that was previously discussed. All possible responses (1-5) were selected for every item. Skewness and Kurtosis for each item and overall score (Skewness=0.03; Kurtosis=3.25) are within the acceptable ranges based on a large sample size (Skewness -2 to +2 and Kurtosis <7) (Kim et al., 2013). Moreover, the means are close to 3 with standard deviations that do not exceed a 2:1 ratio with any other item (Yin, 2016).

		Item-total correlations	Means (SD)	Skewness	Kurtosis
Risk-taking identity (Factor 1)	Item 1	0.73	3.30 (0.893)	-0.55	2.51
	Item 3	0.75	2.76 (0.897)	0.14	2.27
	Item 15	0.68	2.77 (0.576)	-0.22	3.48
FOMO (Factor 2)	Item 2	0.64	3.00 (0.924)	0.03	2.00
	Item 9	0.50	2.56 (0.785)	0.62	2.79
	Item 12	0.47	2.83 (0.907)	0.34	1.96
Preference for certainty (Factor 3)	Item 4	0.66	2.61 (0.831)	0.57	2.39
	Item 8	0.69	2.61 (0.825)	0.70	2.54
	Item 10	0.66	2.89 (0.841)	0.20	2.02
Uncertainty tolerance (Factor 4)	Item 5	0.58	3.25 (0.861)	-0.43	2.19
	Item 6	0.56	3.42 (0.851)	-0.61	2.41
	Item 7	0.60	3.34 (0.797)	-0.43	2.40
Emotions towards investing (Factor 5)	Item 11	0.64	3.25 (0.833)	-0.42	2.43
	Item 13	0.57	3.43 (0.894)	-0.90	2.57
	Item 14	0.61	3.34 (0.652)	-0.39	2.70

Table 5: Descriptive statistics of individual items.

7.4 Overall scoring methodology

We believe that a scoring approach where all items carry equal weight is the most robust so that no responses to individual items are able to exert undue influence on the overall risk profile. This approach also ensures that only clients with consistently strong views on the majority of the questions would end up in a very low (1 or 2) or very high (9 or 10) risk band.

8 Additional Testing

To further verify the attitude to risk questionnaire, we examine the distributions between risk profiles 1 to 10 between January 2023 and May 2023. The distribution of clients' risk profiles from the Dynamic Planner attitude to risk questionnaires approximately resembles a normal distribution, with the majority of respondents falling in the risk profile range from 4 – 7 (see Figure 3).

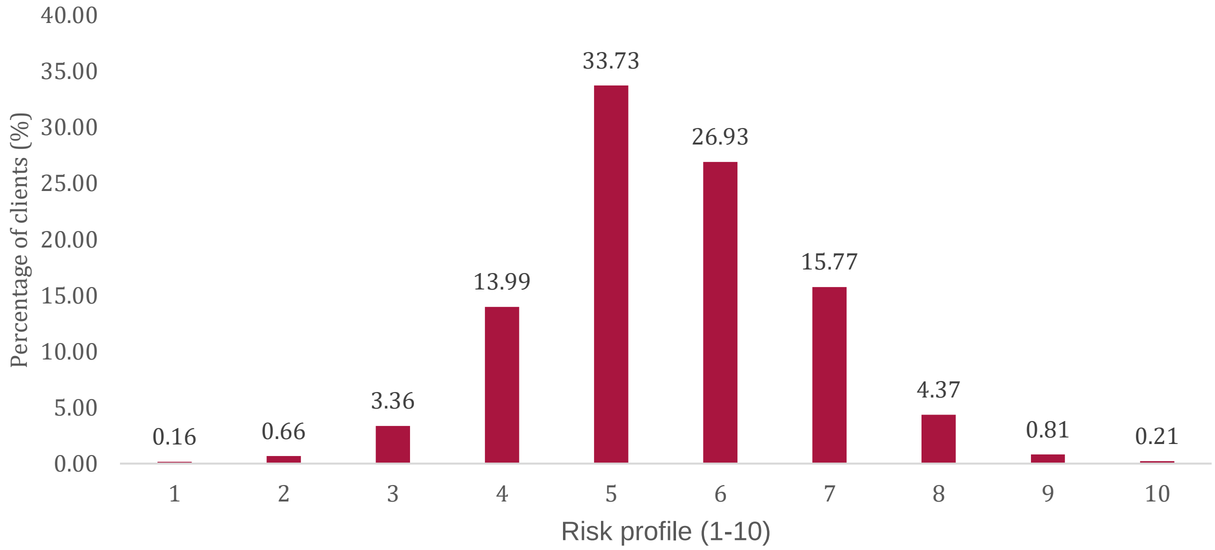

Figure 3: Distribution of risk profiles (Jan 2023- May 2023)

9 Inconsistency Checking

The data used for the initial inconsistency analysis in 2018 was that acquired for stage 3 testing above. As the point of this testing is to find responses where the user has not been fully engaged with the process, the full, unfiltered dataset of 1,037 responders was used. The questionnaire includes flags for excessive non-committal responses, and responses that vary from the overall risk level.

9.1 Excessive middle answers

The ATRQ has 12 questions with a potential answer of “Neither agree nor disagree”. The remaining 3 have been excluded from the middle answer flags, as a middle answer in these cases is not an indication that the question may not have been understood. There are 3 questions in which there is no “neither agree nor disagree” option. It was decided that a middle answer in these questions was not a “non-committal” answer.

It was decided that flags were warranted when more than 60% of responses were middle answers to ensure that responses were not based on a lack of engagement or understanding. Therefore, the questionnaire will flag where respondents have selected “Neither agree nor disagree” for 8 or more of the 12 questions where it is available.

9.2 Single response at variance with overall profile

For each risk level, there is a “consistent range” within which the score to any individual question is deemed “consistent”. An individual question scoring outside this range is flagged as “inconsistent”.

For example, a questionnaire with an overall attitude to risk score of 1 (Lowest risk) would flag any question with a score of 3/5 or higher. The scoring is symmetric, so that a risk level 10 similarly flags any questions scoring 3/5 or lower. Middling risk levels have a wider band of consistent scores, but each risk level can produce inconsistency flags.

An inconsistency flag is not an indicator that an answer is in any way “wrong”. An inconsistency flag is an opportunity for the advisor to talk to the client and ensure they understand the questions and to get any other information required. Where an individual question is frequently flagged, the flags can lose their power, so an analysis of the frequency of a flag appearing for each question was carried out on the data during development stages of the questionnaire where nearly 70% of respondents had no flags at all, 17% had only 1 and only 13% had more than 1 flag.

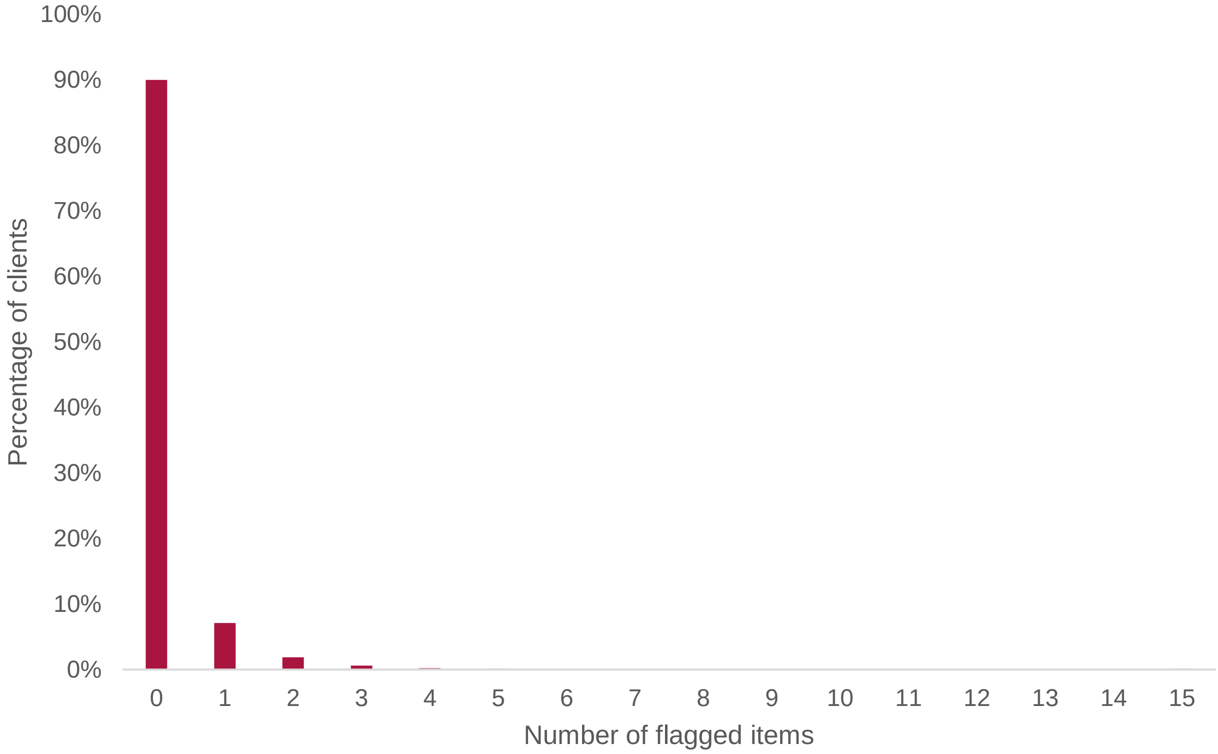

Figure 4: ATR15 number of flagged questions (Jan 2023- May 2023)

Inconsistency data from January to May 2023 shows that we continue to observe that a high proportion of clients respond consistently to all questions when assessing their attitude to risk (90%). Only 10% are receive an inconsistent flag and of these, 7% have 1 flag and 3% more than 1 (see figure 4).

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