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# The Role of Fear of Missing Out and Experience in the Formation of SME Decision Makers' Intentions to Adopt New Manufacturing Technologies

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ABSTRACT

Corporate decision-makers form their intention to adopt new technology for their venture based on their perception of its usefulness and ease of use. However, the formation of this intention might be influenced by the fear of missing out (FOMO), making decision-makers fear losing their relatedness with fellow managers and leading to decisions based on irrational considerations. We draw on and extend the technology acceptance model to explain the potential bias caused by FOMO and expect that this bias is contingent on the level of decision makers' prior experience with the new technology in other contexts. Moderated OLS regressions on 514 observations collected from a representative sample of decision-makers of Austrian SMEs show that FOMO is positively related to the intention to adopt new technology. Moreover, we find that the relationship is mitigated by the decision maker's prior experience with that new technology. We highlight the relevance of the FOMO bias in technology acceptance, adding to the growing research stream on the role of emotions in adopting novel technologies. We further show how experience can effectively counter the FOMO bias for many decision-makers and extend the scope of technology acceptance models by illustrating their applicability to novel manufacturing technologies.

## 1. INTRODUCTION

Corporate decision makers are increasingly faced with the challenge of making decisions on adopting or rejecting new manufacturing technologies in which they have limited experience. Because such decisions strongly impact the further development of the company, they are often exacerbated by social, emotional, and psychological factors (e.g., Hartwick & Barki, 1994; Tomasino & Fedorowicz, 2014; Yang & Bahli, 2014). A well-established framework used to capture the intention to adopt new technology is the technology acceptance model (TAM) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh, 2000). TAM builds on the principles of the theory of reasoned action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and the theory of planned behavior (Ajzen, 1991) with the basic assumption that individuals act rationally in basing their adoption decisions on a technology's perceived usefulness and perceived ease of use (Davis, 1989; Kim, Mirusmonov, & Lee, 2010). The core theory was later expanded over and above rational factors by for example social pressure induced by fashions and hype (Jun, 2012; Swanson, 2012; Tomasino & Fedorowicz, 2014) as well as emotions such as happiness or anxiety (Beaudry & Pinsonneault, 2010; Venkathesh et al., 2003).

We expand this stream of research on TAM further. We not only add an additional factor to TAM by introducing the fear of missing out (FOMO) as a bias in managerial decisions on new manufacturing technologies, but also provide a solution by explaining how prior experience with a new technology can reduce the FOMO bias. FOMO can be conceptualized within self-determination theory (SDT) as the negative emotional state that manifests when individuals perceive their relatedness with their peer group to be threatened (Elhai et al., 2018). Self-determination theory holds that relatedness is one of three innate psychological needs that determine an individual's psychological well-being (Deci & Ryan, 1985; Ryan & Deci, 2000). FOMO is pervasive in individuals and leads to irrational behavioral changes (Elhai, Levine, Dvorak, & Hall, 2016) as has been shown for areas such as smartphones, the internet, or social media (Abel, Buff, & Burr, 2016; Alt & Boniel-Nissim, 2018; Beyens, Frison, & Eggermont, 2016; Elhai et al., 2018;

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Przybylski et al., 2013), human resource management (Budnick, Rogers, & Barber, 2020; Cristea & Leonardi, 2019), finance (Clor-Proell, Guggenmos, & Rennekamp, 2020; Carreyrou, 2018), and marketing (Good & Hyman, 2020; Celik, Eru, & Cop, 2019; Saleh, 2012¸ Kang et al., 2019). Nevertheless, research into the role of FOMO in individuals' decision-making on the adoption of new technology is a recent departure (Koens et al., 2021; Wolniewicz, Tiamiyu, Weeks, & Elhai, 2018). This study adds to this emergent stream of literature being the first empirical study focusing on the economically highly relevant acceptance decision on new manufacturing technologies.

We argue that corporate decision makers' fear to lose their relatedness with fellow managers because of not joining the bandwagon towards a new manufacturing technology may motivate them to adopt these technologies in the firm over and above what is warranted based on their rational considerations. We further argue that an individual's experience with a new technology prior to adoption is positively linked to his or her usage intention (Manis & Choi, 2019; Szajna, 1996; Thompson, Higgins, & Howell, 1994) because managers form habits and routines (Kim & Malhotra, 2005; Tambe et al., 2012) and feel more comfortable with technologies they already know from other contexts (Shane, 2000; Rogers, 1995). More importantly, we argue that experience is buffering the positive relationship of FOMO and intention to adopt the new manufacturing technology. Here, the rationale is that experience implies reduced decision uncertainty, which in turn is associated with reduced relevance of emotional factors in comparison with rational factors in the managerial decision to adopt a new manufacturing technology (Simon, 1987; Feldman et al., 1998).

To empirically test these arguments, we complement the core TAM variables with the ten items delimiting FOMO suggested by Przybylski, Murayama, DeHaan, and Gladwell (2013) and survey decision makers' experience and intentions to adopt additive manufacturing (AM)—an emerging manufacturing technology better known as 3d printing. The survey data used derive from 514 observations from a representative sample of decision makers of small and medium-sized enterprises (SMEs) in Austria.

Our moderated OLS regression shows that FOMO is positively related to the intention to adopt a new technology and that the relationship is weakened by the prior experience the decision maker has in relation to that new technology. Subgroup analyses identify the boundaries of our results. While the FOMO bias and experience are relevant across all subgroups, the buffering effect of experience for the FOMO bias, applies to the specific subgroups of decision makers who are very open to new technologies, who are well educated (i.e., who have a university degree) and who work in the sectors of craft and industry. Overall, our findings highlight the empirical relevance of the FOMO bias in technology adoption and of the moderating role of experience.

Our results contribute to research on TAM in three specific ways. First, we highlight the relevance of the FOMO bias in SME decision makers' individual decisions on implementing a new manufacturing technology in the firm. This insight adds to the growing research stream on the role of emotions in the implementation of novel technologies (Atabek, 2020; Lu et al., 2019; Przybylski et al., 2013; Beaudry & Pinsonneault, 2010; Venkathesh, 2000). Second, we suggest prior experience with the novel technology as an effective measure to counter the FOMO bias for many SME decision makers. This learning links to well-established concepts such as experiential learning by doing (Adler and Clark, 1991) for overcoming knowledge barriers for the use of novel technologies (Nambisan & Wang, 2000; Ravichandran, 2001). Third, we extend the scope of TAM by highlighting that the FOMO bias is not only relevant for end-users of consumer products and services such as smartphone, internet, or social media but also for corporate decision makers in their decision on implementing novel manufacturing technologies. We discuss potential implications and propose an agenda for further research.

## 2. THEORETICAL BACKGROUND AND HYPOTHESES

### 2.1. Technology Acceptance

Why do individuals adopt new technologies? This question has long been explored in theory and practice. Among the most popular models analyzing individual adoption intentions and decisions is the TAM, which draws on the theory of reasoned action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and the theory of planned behavior (Ajzen, 1991) and investigates the determinants of an individual's intention to adopt new technologies. Intentions mediate the cognitive antecedents of behavior (Ajzen, 2011). The TAM was introduced by Davis (1989) and Davis et al. (1989) with the goal of exploring the use of information technology in the workplace. Since then, the TAM has been applied to a wide range of technologies, with an emphasis on consumer technologies, such as digital music players (Song et al., 2009), mobile payment applications (Schmidthuber et al., 2018), virtual-reality hardware (Manis & Choi, 2019), and autonomous driving (Nastjuk et al., 2020). Applications to examine B2B technologies include library management systems (Kurniasih et al., 2019), e-banking technologies (Giatsidis & Kamariotou, 2021), agricultural information technology (Ya-na et al. 2019) and service robots (Stanislav et al. 2020). The model has also been used to investigate the conditions in which technology is used (e.g., Parry et al., 2012; Venkatesh, 2000), the role of age (Venkatesh et al., 2002) and gender (Venkatesh & Morris, 2000), as well as cultural factors (Phillips et al., 1994; Straub et al., 1997). However, to the best of our knowledge, the TAM has not yet been applied to manufacturing technologies.

One of the key assumptions of the TAM is that individuals act rationally when forming the intention of whether to adopt a new technology (Kim et al., 2010). Individuals base their intention to adopt a new technology on two fundamental determinants–perceived usefulness and perceived ease of use. Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Hence, individuals are only willing to adopt a new technology if they expect the new technology to provide unique benefits over existing solutions (Rogers, 2003). Perceived ease of use describes "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). It is, thus, tied to an individual's assessment of the effort involved in understanding and using a new technology (Venkatesh, 2000). If people believe a new technology requires too much effort to understand and to use, they may refrain from using it. Our baseline assumption is therefore that both the perceived usefulness of the new technology and the perceived ease associated with its use impact an individual's intention to adopt that technology.

### 2.2. The role of FOMO

Extensions of the TAM incorporated emotions and psychological states in addition to the rational factors, such as computer anxiety (Venkatesh, 2000) and technology addiction (Turel, Serenko, & Giles, 2011) that can influence the intention to adopt a new technology by affecting perceptions about the use of that technology (Venkatesh, 2000). One emotion that warrants consideration in the context of technology acceptance is the fear of missing out (FOMO), which describes the "pervasive apprehension that others might be having rewarding experiences from which one is absent" (Przybylski et al., 2013, p. 1841). Individuals fear to miss desirable opportunities and therefore strongly and constantly desire to stay connected with what others are doing (Zhang, Jiménez, & Cicala, 2020). Self-determination theory (SDT) suggests that an individual's psychological well-being results from the satisfaction of three innate psychological needs—competence, autonomy, and relatedness (Deci & Ryan, 1985; Ryan & Deci, 2000). Within SDT, FOMO can be conceptualized as a negative emotional state that manifests when individuals perceive their relatedness with their peer group to be threatened (Elhai et al., 2018). Accordingly, individuals who perceive their relatedness with their peer group at risk experience higher levels of FOMO and, therefore, try to find ways to regulate their psychological well-being (Przybylski et al., 2013).

That process of regulating their psychological well-being often entices individuals experiencing higher levels of FOMO to mimic their peers. Individuals are surprisingly willing to change their behavior to regulate their psychological well-being in response to FOMO (Kang, Cui, & Son, 2019). For example, when their peers use smartphones, the internet, or social media, they also use smartphones, the internet, or social media. This effect even makes individuals use technologies excessively when their peers use them extensively (e.g., Abel, Buff, & Burr, 2016; Alt & Boniel-Nissim, 2018; Beyens, Frison, & Eggermont, 2016; Elhai et al., 2018; Przybylski et al., 2013). The FOMO has been shown to impair rational considerations in many different contexts. For example, individuals who fear missing out show more extreme responses and a lack of constructive problem solving when digital technologies fail, suggesting that preventing access to these technologies may cause severe anxiety (Hadlington & Scase, 2018). In the work context, FOMO in employees dislocated from the office due to travel or remote work leads to extensive message checking behavior and constant signaling of commitment in fear of losing the relatedness with their peers up to a degree that causes burnout symptoms and impairs their personal lives (Budnick, Rogers, & Barber, 2020; Cristea & Leonardi, 2019). In the context of risk capital investments, FOMO impacts on project assessments and causes excessive information-seeking behavior (Clor-Proell, Guggenmos, & Rennekamp, 2020) and irrational investment decisions (Carreyrou, 2018). In the marketing context, FOMO increases impulse purchasing (e.g., Good & Hyman, 2020), which in turn leads to post-purchase regrets (e.g., Celik, Eru, & Cop, 2019; Saleh, 2012). The rationale is that a purchase decision is also a decision to belong to a particular peer group and a positive purchase decision is, therefore, motivated by the fear of being excluded from such a group (Kang et al., 2019).

The theoretical considerations and empirical evidence suggest that individuals who fear missing out the relatedness to their peers engage in behavior intended to combat this fear (Pentina, Koh, & Le, 2012; Hartwick & Barki, 1994; Ram & Jung, 1991). The effect of FOMO motivating a certain behavior over and above rational considerations can be interpreted as a bias. In face of FOMO, a certain behavior is shown more often or more intensively than would be warranted on rational grounds. This FOMO bias is amplified when the available option (i.e., a market offer, an investment, or a technology) is subject to hypes (Angst et al., 2010; Jun, 2012; Swanson, 2012; Tomasino & Fedorowicz, 2014; Wang, 2010; Hayran et al., 2020). Not only novel technologies in consumer products signal the belonging to specific societal peer groups and are subject to hypes. Also new manufacturing technologies such as additive manufacturing are subject to communities of corporate decision makers and undergo hype cycles (Shanler & Basiliere, 2019). Thus, we argue that corporate decision makers' fear to lose their relatedness with fellow managers because of not joining the bandwagon towards a new manufacturing technology may motivate them to adopt these technologies over and above what is warranted based on their rational considerations. Based on these arguments we formulate our first hypothesis:

**H1**: FOMO is positively related to the intention to use a new manufacturing technology.

### 2.3. The role of experience

An individual's experience with a new technology can positively influence his or her usage intention (Manis & Choi, 2019; Szajna, 1996; Thompson, Higgins, & Howell, 1994) and later adoption (Compagni et al., 2015). Experience benefits individuals making decisions by allowing them to choose the technology with the greatest benefit for them (Dishaw & Strong, 1999). Experience acquired prior to adoption, gained through education or practical experience with the technology in a private context, in a previous occupation or through external service providers allows individuals to acquire information and learn more about the technology's strengths and weaknesses (Hartwick & Barki, 1994; Gielnik et al., 2015). Each new piece of information acquired through experience helps individuals to adjust their intentions (Doll & Ajzen, 1992) not only via conscious decision-making processes but also via routines and habits (Kim & Malhotra, 2005; Tambe et al., 2012). Independently for the nature of the experience, corporate decision makers tend to stick to what they know because it makes them feel comfortable and secure (Miles & Snow, 1978). In decisions on new technologies, corporate decision makers are likely to favor options they know over options that are novel to them (Shane, 2000). Past experience shapes future behavioral decisions (Rogers, 1995). Those who have experience with a novel technology outside the firm have made a positive adoption decision on this technology before. What has been evaluated as useful and easy to use in other applications in the past is likely to be evaluated similarly positively for other applications later. Thus, prior experience with a similar technology influences the intention to use this technology in future applications (Lippert and Forman, 2005). We therefore propose the following hypothesis:

**H2**: The level of previous experience with a new manufacturing technology is positively related to the intention to use that new manufacturing technology.

Alongside the direct relationship between experience and usage intention, experience can also moderate the relationship between FOMO and usage intention. Knowledge about a novel technology reduces uncertainty in the decision on the implementation of this technology (Ravichandran, 2001). Thus, the more corporate decision makers know about the technology they consider adopting, the less uncertainty they perceive in relation to the decision (Ghadim et al., 1999). They are less uncertain regarding the next steps they need to take in the adoption process (action uncertainty) and regarding the opportunity costs implied by giving up alternative technologies (action doubt). At the same time, they know more about the consequences of the adoption (van Gelderen et al., 2015; McKelvie et al., 2011; McMullen & Shepherd, 2006). Interestingly, the less uncertain decision makers are in their adoption decision, the more important are the rational elements–such as performance indicators of the new technology in question–in comparison to the emotional elements–such as FOMO–in the decision-making process (Simon, 1987; Feldman et al., 1998). The more experience individuals have with a technology, the less their intention to use that technology is driven by FOMO. Thus, experience is buffering the positive relationship of FOMO and the intention to adopt the new manufacturing technology. We therefore propose the following hypothesis:

**H3**: The level of previous experience with a new manufacturing technology moderates the relationship between FOMO and the intention to use that new manufacturing technology, such that a rising level of experience weakens the relationship.

## 3. METHOD

### 3.1. Data Collection

The empirical analysis is based on primary survey data collected from a regionally stratified random sample of Austrian SMEs. Regional stratification is necessary because in Austria institutional settings differ considerably among regions. Our regional stratification followed the approach suggested by Kibler, Kautonen, and Fink (2014) and involved collecting data in 27 municipalities randomly sampled in three categories—urban, semi-urban, and rural (Statistik Austria 2011)—across all nine federal states of Austria early in 2019. We identified 185,535 firms in the Aurelia database provided by Bureau van Dijk with valid contact information, with at least one but not more than 249 employees, that were active in industry, craft, service & trade, research, training, and administration. Among those firms, 151,361 were SMEs and 52,845 were registered in the 27 selected municipalities. We extracted a random sample of 7,286 firms from those 52,845 firms that was weighted for firm size (one-third from each size category: micro, small, and medium).

Each sampled firm was contacted to identify an interview partner with decision power on the manufacturing technologies used in the firm. In micro and small firms, that contact was likely to be the founder and/or CEO, while in medium-sized firms we welcomed members of the top management team as respondents. Data were collected with computer-aided telephone interviews. To give the firms a similar chance to participate in the survey, we made three contact attempts with each firm, which resulted in 585 responses. The response rate of 8 % is a little below average but in line with similar studies that randomly addressed decision makers with detailed questionnaires (Poynton, DeFouw, & Morizio, 2019; Sauermann & Roach, 2013). Following the removal of observations with missing values our analysis is based on a sample of 514 cases.

We addressed potential nonresponse bias at the survey design stage by carefully designing the questionnaire to maintain the respondent's interest, keeping it to a reasonable length, and establishing the importance of the study in the introductory email (Yu & Cooper, 1983). We also assessed the analytic sample for potential nonresponse bias using two techniques, each targeting a specific type of nonresponse (Rogelberg & Stanton, 2007). First, we implemented the archival approach, which compares the characteristics of the sample with those of the population. This approach is particularly suitable for identifying passive nonresponse, which results from external factors hindering the recipients from returning the completed questionnaire on time. Passive nonresponse typically accounts for 85 % of total nonresponse (Sosdian & Sharp, 1980). For our sample, we used the respondents' age, gender, and education level for archival analysis, as these variables have been shown to influence the intention to use new technologies (Przybylski et al., 2013) and because the information was available for the population of Austrian SME decision makers (Gavac & Fürst, 2019; Statistik Austria, 2020). The comparison identified only a minor under-sampling of women and the education level was slightly higher in the sample than in the relevant population, accordingly, passive nonresponse does not seem to be a major concern. Second, we applied wave analysis to compare the results from early and late respondents, which is especially useful for controlling active nonresponse, which refers to a conscious decision not to participate in a study (Rogelberg et al., 2003). For our sample, the wave analysis did not identify any significant differences between early (first half) and late (second half) respondents, and hence we conclude that active nonresponse bias is not an issue in our sample.

## 3.2. Variables

### 3.2.1. Independent variables

We used validated reflective measurement models to capture the dependent and independent variables. Specifically, in our operationalization, we follow the TAM (Davis, 1989; Davis et al., 1989), which is the most widely applied model used to capture individuals' acceptance and usage of available technologies (Venkatesh, 2000). The TAM is an information system theory that builds on Fishbein and Ajzen's (1975) theory of reasoned action (TRA), which measures technology acceptance based on two variables, *Perceived ease of use* and *Perceived usefulness*. The current study adopts those two variables as its first two independent variables. The first, perceived usefulness, reflects the degree to which a person believes that using a particular technology would enhance their job performance. We measure usefulness using four items with an example being "Using additive manufacturing in my job increases my productivity." The second independent variable, perceived ease of use, reflects the degree to which a person believes that using a particular technology would require little effort. We use four items to measure ease of use with one example being "I find additive manufacturing to be easy to use." We complement the core TAM variables with the fear of missing out (FOMO) as our third independent variable. To measure FOMO, we use the original ten items suggested by Przybylski et al. (2013). A sample item is "It bothers me when I miss an opportunity to meet other people from my industry." For each item, respondents indicated their degree of agreement on a 7-point Likert-style scale anchored with "I do not agree at all" (1) and "I completely agree" (7).

### 3.2.2. Moderator variable

In our theoretical model, we argue that the relationship between FOMO and the intention to use AM is moderated by the level of experience SME decision makers have with AM technology in other contexts prior to adoption in their firm. We operationalize *Experience* as a three-point categorial variable with high values representing a high level of experience.

### 3.2.3. Dependent variable

The model is set up to explain the intention of SME decision makers to use AM as a new manufacturing technology. In this study, the dependent variable is *Intention to use AM* (Davis, 1989; Davis et al., 1989). Additive manufacturing is but one example of an archetypal emerging manufacturing technology with intensive media attention and moderate current market value (Maresch & Gartner, 2020). We address the call by Ajzen (Tornikoski & Maalaoui, 2019) that researchers using TPB/TRA should define a temporal frame for an intended behavior by applying a twelve-month outlook. To capture SME decision makers' intention to use AM in their firm, we use a three-item scale; accordingly, a sample item is "I plan to use additive manufacturing in the next 12 months." As with the independent variables, the respondents indicated the extent to which they agreed with statements relating to the dependent variable on a 7-point Likert-style scale anchored with "I do not agree at all" (1) and "I completely agree" (7).

### 3.2.4. Control variables

We controlled for the respondents' biological age, sex, and education level because these aspects have been shown to influence the intention to use available technology (Venkatesh & Morris, 2000; Venkatesh et al., 2002).

## 3.3. Common Method Bias

Prior research highlights the threat of *common method bias* (CMB) affecting empirical research relying on cross-sectional data (Lindell & Whitney, 2001), and especially for the most common self-report surveys where the dependent and independent variables are cognitions (Harrison, McLaughlin, & Coalter, 1996). Several *ex-ante* and *ex-post* measures have been suggested to address the risk of CMB (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). However, Spector (2006) and Richardson, Simmering, and Sturman (2009) provided compelling evidence showing that *ex-post* statistical measures used to adjust analyses to account for CMB are unreliable and often misleading, which prompted the use of strategies to avoid CMB *ex-ante* in this study. First, we protected the respondents' anonymity, thus mitigating evaluation apprehension (Podsakoff et al., 2003). Second, we used different question formats and randomized the order of scales in the questionnaire.

## 3.4. Analysis Strategy and Diagnostics

We ran a moderated OLS regression using a stepwise approach. In the first step, we entered the control variables in the model. In the second step, we added the three dependent variables, and in the third step, we added the interaction term. In the interpretation of the results, it must be kept in mind that our analysis is based on a cross-sectional dataset, which does not allow for testing causalities but associations.

Before performing the final estimations, we examined the model for multicollinearity. The highest variance inflation factor score was 1.53, which is clearly below the conventional threshold of 10 indicating serious multicollinearity.

### 3.5. Descriptive Statistics

Table I shows the means, minima, maxima, standard deviations, and the correlation matrix for all variables used in the analysis. We do not detect any unexpected correlations.

### 3.6. Results

Table II presents the results of the OLS regression models. Model 1 includes the control variables alone; Model 2 shows the direct relationships of all variables (the TAM baseline assumptions as well as Hypotheses 1 and 2), and Model 3 adds the interaction term (Hypothesis 3).

Model 1 shows that among the control variables biological age and sex are significantly related to the intention of SME decision makers to use AM in the 12 months following the survey. In line with our expectations, young male respondents report stronger intentions to use AM compared to female and older respondents.

Model 2 adds all independent variables to the equation. In the baseline assumptions rooted in the TAM, we expected perceived usefulness and perceived ease of use to be positively related to SME decision makers' intention to use AM in the coming 12 months. We find that both perceived usefulness (ß=.275; p=.000) and perceived ease of use (ß=.267; p=.000) are significantly and positively related to the intention to use AM. This result confirms our baseline assumptions.

The first hypothesis expressed an expectation that the fear of missing out (FOMO) would be positively related to SME decision makers' intentions to use AM in the coming 12 months. We find that FOMO is significantly and positively (ß=.137; p=.000) related to the intention to use the new technology. This result supports our first hypothesis (H1).

The second hypothesis expressed an expectation that the level of experience with the new technology gained prior to adoption would be positively related to SME decision makers' intentions to use that new technology in the coming 12 months. We find that the level of experience is significantly and positively (ß=.325; p=.000) related to the intention to use the new technology. This result supports our second hypothesis (H2).

Model 3 adds the interaction term. For the parsimony of the presentation, we include only the significant interaction term in the model presented in Table II. The third hypothesis expressed an expectation that the level of experience prior to adoption with the new technology would moderate the relationship between FOMO and SME decision makers' intention to use that new technology in the following 12 months, such that a rise in the level of experience weakens the relationship. We find that the interaction term is significant and has a negative sign (ß=-.100; p=.003). To ease interpretation, we plotted the interaction term (Fig. I), which indicated that under the condition of low levels of experience, FOMO among SME decision makers is more strongly linked to the intention to use the new technology than under the condition of a high levels of experience. Experience with the new technology therefore has a buffering effect on the relationship between FOMO and the intention to use the technology. This finding supports Hypothesis 3.

In addition, to identify the boundaries of our results we perform subgroup analysis for those sectors that were populated with a sufficient number of observations, for different levels of education and of openness to new technologies (Table II). The subgroup analysis reveals that the FOMO bias and experience are relevant across all subgroups. The buffering effect of experience on the FOMO bias, however, applies to the specific subgroups of decision makers who are very open to new technologies, who are well educated (i.e., who have a university degree) and who work in the sectors of craft and industry.

## 4. DISCUSSION AND CONCLUSION

This study examined decision makers' intentions to adopt a novel manufacturing technology in their SME. Specifically, it theoretically argued and empirically tested the relevance and interplay of the FOMO bias and the decision maker's experience with a novel manufacturing technology acquired prior to adoption for such decisions. We use AM as an example of such a new manufacturing technology. Our theoretical reasoning builds on the TAM.

We argue that corporate decision makers fear to lose their relatedness with fellow managers because they fail to join the crowd towards a new manufacturing technology. This FOMO may motivate them to adopt a novel technology that is popular among their peers in their firm, over and above what is warranted based on their rational considerations. Further, we propose that corporate decision makers' intention to adopt a new technology also depends on their experience with this technology prior to adoption (Manis & Choi, 2019; Szajna, 1996; Thompson, Higgins, & Howell, 1994). This is because for a specific application decision makers are likely to make a positive evaluation of a new technology if this technology has proven to be useful and easy to use in other applications in the past. The last step in our argumentation is that decision makers' prior experience with a novel manufacturing technology is buffering the positive relationship between FOMO and intention to adopt it in the firm. We explain the moderation effect with the reduced relevance of emotional factors in less uncertain decisions. Experience implies reduced decision uncertainty, which in turn is associated with reduced relevance of emotional factors in comparison with rational factors in the managerial decision to adopt a new manufacturing technology (Simon, 1987; Feldman et al., 1998). Accordingly, we hypothesized that (1) FOMO is positively related to the intention to use a new manufacturing technology, that (2) the level of prior experience with the new manufacturing technology is positively related to the intention to use that new manufacturing technology, and that (3) the level of prior experience with a new manufacturing technology moderates the relationship between FOMO and the intention to use that new manufacturing technology, in a way that a rise in the level of experience weakens the relationship.

Our OLS regression model confirmed our baseline assumptions rooted in the TAM that perceived usefulness and perceived ease of use are positively related to SME decision makers' intention to use novel

**Table I**
Descriptive statistics

| | α | Min | Max | Mean | SD | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Education level | | 1 | 4 | 3.89 | 1.225 | 1.000 | | | | | | | |
| 2. Biological age | | 24 | 78 | 41.53 | 12.411 | 0.082* | 1.000 | | | | | | |
| 3. Biological sex (1=male, 2=female) | | 1 | 2 | 1.18 | .481 | 0.152** | -0.110* | 1.000 | | | | | |
| 4. Intention to use AM | .849 | .67 | 7 | 3.8811 | 1.70524 | -0.021 | -0.027 | 0.135* | 1.000 | | | | |
| 5. Usefulness | .958 | 0 | 7 | 4.2995 | 2.26159 | 0.551** | -0.030 | 0.201** | 0.072 | 1.000 | | | |
| 6. Ease of use | .910 | 0 | 7 | 3.6735 | 1.76458 | 0.467** | -0.027 | 0.221** | 0.089* | 0.430** | 1.000 | | |
| 7. Fear of missing out (FOMO) | .911 | | | 4.0576 | 1.64806 | 0.230** | 0.113* | 0.036 | 0.144* | 0.206** | 0.105* | 1.000 | |
| 8. Level of experience with AM | | | | 1.9659 | 1.68319 | 0.519** | 0.126* | 0.205** | -0.070 | 0.439** | 0.239** | 0.041 | 1.000 |

Notes: n=514. Pearson correlation coefficients. * and ** denote significance at the 5 % and 1 % levels. α = Cronbach's alpha

**Table II**
Test of Hypotheses and robustness checks

| | Test of hypotheses | | | | | | Robustness checks | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Sector | | | | | | Openness towards new technologies | | | | Education | | | |
| | Model 1 (n=514) | | Model 2 (n=514) | | Model 3 (n=514) | | Industry (n=109) | | Craft (n=95) | | Service and Trade (n=209) | | Very open (n=263) | | Not very open (n=247) | | No university degree (n=253) | | University degree (n=258) | |
| | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p |
| Education level | -.041 | .355 | -.057 | .084 | -.050 | .128 | -.017 | .811 | .132 | .110 | .052 | .308 | .012 | .787 | .072 | .208 | | | | |
| Biological age | .100 | .023 | .037 | .260 | .041 | .215 | -.040 | .553 | -.110 | .177 | .062 | .238 | -.021 | .628 | -.021 | .723 | .010 | .834 | .069 | .140 |
| Biological sex (1=male. 2=female) | .169 | .000 | -.021 | .529 | -.025 | .452 | -.036 | .582 | -.139 | .087 | -.016 | .758 | .016 | .707 | -.103 | .064 | -.031 | .528 | -.014 | .763 |
| Usefulness | | | .275 | .000 | .265 | .000 | .165 | .041 | .377 | .000 | .249 | .000 | .324 | .000 | .179 | .005 | .282 | .000 | .224 | .000 |
| Ease of use | | | .267 | .000 | .263 | .000 | .319 | .000 | .272 | .001 | .333 | .000 | .230 | .000 | .283 | .000 | .201 | .000 | .312 | .000 |
| Fear of missing out (FOMO) | | | .137 | .000 | .161 | .000 | .257 | .001 | .242 | .002 | .113 | .029 | .185 | .000 | .166 | .005 | .120 | .014 | .208 | .000 |
| Level of experience with AM | | | .325 | .000 | .313 | .000 | .443 | .000 | .179 | .044 | .284 | .000 | .328 | .000 | .223 | .000 | .371 | .000 | .296 | .000 |
| Subjective Norms | | | | | | | | | | | | | | | | | | | | |
| FOMO* Level of experience with AM | | | | | -.100 | .003 | -.151 | .062 | -.196 | .024 | -.065 | .199 | -.141 | .004 | -.074 | .192 | -.044 | .395 | -.129 | .005 |
| FOMO* Subjective Norms | | | | | | | | | | | | | | | | | | | | |
| R-squared | .035 | | .477 | | .486 | | .559 | | .496 | | .496 | | .546 | | .291 | | .468 | | .491 | |
| Δ R-squared compared to previous model | | | .442 | | .009 | | | | | | | | | | | | | | | |
| Chi-squared test for change in model fit (compared to previous model) | 6.130 (3 df) p=.000 | | 106.994 (4 df) p=.000 | | 8.737 (1 df) p=.003 | | | | | | | | | | | | | | | |

Notes: Number of cases vary between models due to missing values. Dependent variable: Intention to use AM. df = degrees of freedom

manufacturing technology in their firm. Most importantly, we found FOMO as well as prior experience are positively related to SME decision makers' intentions to use new technology and that prior experience can buffer the FOMO bias. Interestingly, FOMO bias and experience are relevant across all subgroups. However, the buffering effect of experience for the FOMO bias applies to three specific subgroups of decision makers. These subgroups include decision makers who are very open to new technologies, who have a high level of education (i.e., a university degree), and who work in the sectors craft and industry.

The findings show that FOMO pushes SME decision makers towards the implementation of novel manufacturing technology. Thus, even with similar evaluations of the usefulness and ease of use of a novel manufacturing technology, when SME decision makers have high levels of FOMO, they also have stronger intentions to adopt this novel manufacturing technology. FOMO seems to be an extrafunctional attribute (Priem et al., 2012) of the novel technology as a positive decision to implement the novel manufacturing technology adds emotional value to managers over and above the rational arguments based on functional attributes. The FOMO bias identified in this study confirms recent findings by Schillebeeckx et al (2022) on how managers choose novel materials for manufacturing technology choices. It helps explain managerial investment decisions in new technologies that–from a rational point of view–were made too early or based on too weak rationales. However, it is important to note that a bias towards the adoption of new manufacturing technologies does not imply disadvantageous management decisions. It rather means that rational arguments (not yet) warrant such a managerial decision. Thus, the FOMO bias can result in SMEs becoming successful frontrunners for a novel manufacturing technology but also in existence-threatening misinvestments. These insights show that the FOMO bias is not only a phenomenon relevant for end-users of consumer products and services such as smartphone, internet, or social media usage (e.g., Abel et al., 2016; Alt & Boniel-Nissim, 2018; Beyens et al., 2016; Elhai et al., 2018; Przybylski et al., 2013) but also in management professionals (Good & Hyman, 2020).

Our results also provide an effective measure for mitigating the potential threat of FOMO bias. Rising levels of prior experience with a new manufacturing technology buffer the FOMO bias in SME decision makers. However, subgroup analyses have revealed important boundary conditions for this buffering effect. First, the buffering effect shows among SME decision makers who are very open to new technologies. A lack of openness to new technologies apparently blocks experienced-based learning (Adler and Clark, 1991) that would reduce uncertainty and, thus, the relevance of emotional factors such as FOMO in the decision to implement the novel technology. Formal education seems to enable experienced-based learning in SME decision makers. We find the buffering effect of prior experience with a novel manufacturing technology on the FOMO bias among those SME decision makers in our sample who hold a university degree. Finally, prior experience with a novel manufacturing technology is only an effective measure to counter the FOMO bias for SME decision makers who work in the sectors craft and industry but not for those who work in service & trade. Because the subsamples of SME decision makers working in the sectors research, training, and administration were too small, we cannot provide a subgroup analysis. However, the buffering effect of prior experience with the novel manufacturing technology seems to be limited to decision makers who work in firms that are directly concerned with manufacturing. In these firms, the introduction of a novel manufacturing technology is more at the core of the business and, thus, risk factors such as unpredictable learning curves and process stability, lack of standards and market approval as well as unreliable technology providers might be more important. With a higher level of risk, prior experience with the envisaged manufacturing technology can more effectively reduce uncertainty and relevance of emotions. However, our findings do not allow for a final interpretation of how sectors matter for the interplay of FOMO bias and prior experience with novel

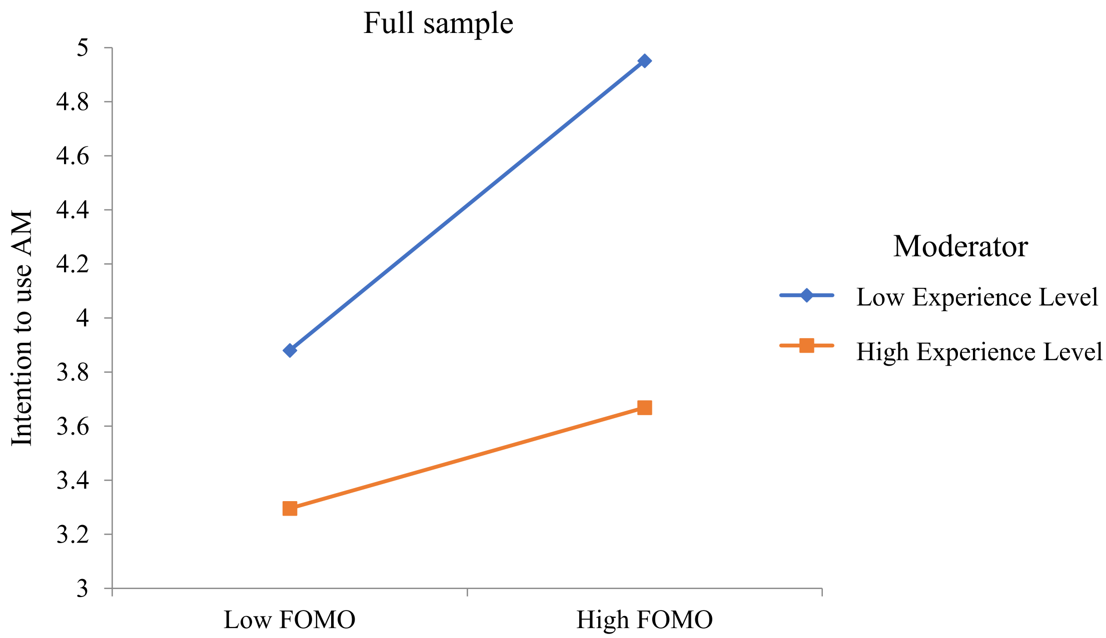


**Fig. 1.** Plots of moderation effects: full sample and subsamples

manufacturing technologies.

Our insights must be interpreted against the backdrop of the limitations of the data used, the analytical strategy followed, and the theoretical background we built upon. Our sample is limited to Austrian SMEs and AM technology. However, Austria offers a good example of a well-developed industrial country with a population of firms that face the constant challenge of keeping up with technological change. AM is a prominent example of an emerging technology that is relevant to almost all industries (Maresch & Gartner, 2020; Wirtschaftsagentur Wien, 2020). To better understand the boundary conditions of our findings, future research should also target other geographical regions and research different technologies and sectors. Moreover, while the scales in our survey instrument employed were designed carefully, social desirability bias and nonresponse bias cannot be completely ruled out. Although the TAM (e.g., Davis, 1989; Venkatesh et al., 2002) offers a valuable theoretical lens, future research could also investigate the institutional context in which firms' adoption of technologies takes place, using different theoretical frameworks such as the Diffusion of Innovation Theory (Moore & Benbasat, 1991; Rogers, 2003). This study only takes an individual-level perspective, which would benefit from being expanded to the market- and organizational-level in future studies to capture cross-level effects.

Notwithstanding the limitations, our findings contribute to research on TAM in three specific ways. First, we highlight the relevance of the FOMO bias in SME decision makers' individual decisions on implementing a new manufacturing technology in the firm. This insight adds to the growing research stream on the role of emotions in the implementation of novel technologies (Atabek, 2020; Lu et al., 2019; Przybylski et al., 2013; Beaudry & Pinsonneault, 2010; Venkathesh, 2000).

Second, we suggest prior experience with the novel technology as an effective measure to counter the FOMO bias for many SME decision makers. This learning links to well-established concepts such as experiential learning by doing (Adler and Clark, 1991) for overcoming knowledge barriers for the use of novel technologies (Nambisan & Wang, 2000; Ravichandran, 2001).

Third, we extend the scope of TAM by highlighting that the FOMO bias is not only relevant for end-users of consumer products and services such as smartphone, internet, or social media but also for corporate decision makers in their decision on implementing novel manufacturing technologies. The successful application of TAM to a manufacturing technology illustrates the model's value for studying technologies well beyond its traditional applications in studies on consumer technologies (Song et al., 2009; Schmidthuber et al., 2018; Manis & Choi, 2019; Nastjuk et al., 2020) or commercial technologies (Kurniasih et al., 2019; Giatsidis & Kamariotou, 2021; Ya-na et al. 2019; Stanislav et al. 2020).

The study contributes to practice by stressing the relevance of the FOMO bias in SME decision makers' intentions to adopt novel manufacturing technologies. As the FOMO bias constitutes both a potential opportunity and a potential threat to the SME decision makers' choice to implement a novel manufacturing technology in the firm it is important that decision makers are aware of this phenomenon. We identified specific subgroups who can mitigate the FOMO bias by acquiring experience with the envisaged manufacturing technology outside the firm prior to making the adoption decision. While we cannot predict the quality of the resulting managerial decision, we could show for well-educated SME decision makers who are concerned with manufacturing and very open to new technologies that with rising levels of prior experience with the envisaged manufacturing technology, rational factors matter more, and emotional factors matter less for SME decision makers' intention to implement this technology in the firm. These decision makers should consider investing in knowledge first and in technology second.

Policymakers can build on our findings by providing corporate decision makers located in the region with low threshold access to new technologies to build up their experience at low risk. Such support, for example, could entail a public-sector agency managing specific public-private partnerships between companies and universities focusing on emerging technologies. These partnerships could include technology platforms on a corporate level or makerspaces on an individual level. The focus of such initiatives could be on the subgroups identified as sensitive to the buffering effect of prior experience on the FOMO bias. The initiatives could advance the dissemination of unbiased knowledge and offer decision makers first-hand experience of emerging technologies for experimental learning (Adler and Clark, 1991). Successful examples in the area of AM are for instance the public-private partnership "America Makes" (www.americamakes.us) and the "fabfoundation" (www.fabfoundation.org). "America Makes" was founded by the US National Center for Defense Manufacturing and Machining (NCDMM) and created a cooperation network between private and public industries. The "fabfoundation" spun off from the Massachusetts Institute of Technology and aims to set up publicly accessible makerspaces.

Future research could build on our findings and examine the impact of FOMO on technologies that are subject to technology hypes to study structural biases affecting technologies that could arise from market and media dynamics. Another interesting aspect would be an investigation of marketing and public relation activities to examine the extent to which FOMO is consciously or unconsciously created or promoted by firms offering new technologies to the market. In addition, our research approach could be extended to other stakeholders such as politicians, funding agencies, and investors to investigate whether FOMO and experience (or the lack thereof) bias their engagement with new technologies. Finally, a follow-up study examining whether the buffering effect of prior experience on the FOMO bias found in this study also affects technology use in areas from which the original FOMO research originates—that of smartphones, the internet, and social media—would also be welcome.

The study concludes that emotions can bias intentions to adopt new technologies and, thus, subsequent decisions. FOMO among decision makers in SMEs seems to be no exception. This research should encourage SME decision makers to first decide on how much to invest in becoming familiar with a new technology and acquiring experience in its use before deciding whether to adopt that technology in the firm. Decision makers acting on this insight are aware of the FOMO bias in their technology adoption decisions and, thus, expedite the development of their SME in times of ongoing technological transformation.

### Authorship contributions

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

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